

# Identification of Bio-climatic Determinants and Potential Risk Areas for Kyasanur Forest Disease in Southern India using MaxEnt Modelling Approach

**Malay Kumar Pramanik**

National Institute of Malaria Research

**Poonam Singh**

National Institute of Malaria Research

**Ramesh C Dhiman** (✉ [r.c.dhiman@gmail.com](mailto:r.c.dhiman@gmail.com))

National Institute of Malaria Research <https://orcid.org/0000-0001-9844-9970>

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## Research article

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# Abstract

**Background:** Kyasanur Forest Disease (KFD), known as monkey fever was for the first time reported in 1957 from Shivamogga district of Karnataka. But since 2011, it is spreading to the neighbouring state of Kerala, Goa, Maharashtra, and Tamil Nadu. The disease is transmitted to humans, monkeys and by the infected bite of ticks *Haemaphysalis spinigera*. It is known that deforestation and ecological changes are the main reasons for KFD emergence, but the bio-climatic understanding and emerging pathways remain unknown.

**Methods:** The present study aims to understand the bio-climatic determinants of KFD tick distribution in southern India using Maximum Entropy (MaxEnt) model. The analysis was done using 34 locations of *Haemaphysalis spinigera* occurrence and nineteen bio-climatic variables from WorldClim. Climatic variables' contribution was assessed using the jackknife test and mean AUC 0.859 which indicated the model performs with very high accuracy.

**Results:** Most influential variables affecting the spatial distribution of *Haemaphysalis spinigera* were the average temperature of the warmest quarter (bio10, contributed 32.5%), average diurnal temperature range (bio2, contributed 21%), precipitation of wettest period (bio13, contributed 17.6%), and annual precipitation (bio12, contributed 11.1%). The highest probability of *Haemaphysalis spinigera* presence was found when mean warmest quarter temperature ranged between 25.4-30°C. The risk of availability of the tick increases noticeably when the mean diurnal temperature ranged between 8-10°C. The tick also preferred habitat having an annual mean temperature (bio1) between 23-26.2°C, mean temperature of the driest quarter (bio9) between 20-28°C, and mean temperature of the wettest quarter (bio8) between 22.5-25°C.

**Conclusions:** The results have established the relationship between bioclimatic variables and KFD tick distribution and mapped the potential areas for KFD in adjacent areas wherein surveillance for the disease is warranted for early preparedness before the occurrence of outbreaks etc. The modelling approach has been found a very useful tool to link bioclimatic variables with present and predicted distribution of *Haemaphysalis spinigera* tick .

## 1. Introduction:

Kyasanur Forest Disease (KFD) is a zoonotic tick-borne viral disease which was first reported from the forested area of Shivamogga district, Karnataka in 1957 [1]. The disease is caused by KFD virus belonging to family *Flaviviridae* and genus *Flavivirus* [2-4]. The virus was found to be highly infectious, as evidenced by several infections in laboratory and field staff [5, 6], which resulted in work suspension until a proper Biosafety Level-3 laboratory was established at NIV in 2004. In nature, the virus is found in ticks, monkeys, shrews, bats and small mammals [7, 8]. KFD is transmitted to animals and humans by the infected tick bites mainly *Haemaphysalis spinigera* [9-12]. The incubation period of KFD virus is ~3–8 days [13].

KFD originates from monkeys [7, 14] which come out to human dwellings and the death of monkeys is an indication for the outbreak in human beings. Monkeys (red faced *Macaca radiata* and black-faced *Presbytis entellus* are the reservoirs of KFD, but they also die due to KFD [8]. It frequently occur in semi-evergreen, evergreen, deciduous and moist forests in southern India only [14] and has also been related with developmental activities resulting into deforestation [15], and ecological changes [8]. Population with occupational exposure to outdoor or rural settings (i.e., herders, hunters, farmers, and forest workers) in the villages are potentially at risk of the disease if get contact with infected *Haemaphysalis spinigera* ticks [3, 8]. The disease prevails from November to May when the nymphs' density is maximum in the forest due to favourable moisture in the soil of forest areas [16-18]. The disease is localized in several districts, namely and Chikmagalur, Shivamogga, Udupi, Dakshina and Uttar Kannada of the Karnataka state, India [6, 12]. Since the first reporting of the disease from Shivamogga district in 1957, several sporadic cases and outbreaks have been reported every year in the same region [4, 7, 19, 20]. But, in the past few years, (i.e., 2013 onwards) the geographical range of the disease has extended to the districts in Kerala, Goa, Maharashtra, and Tamil Nadu (Fig 1).

The reason of spread of KFD to near areas are not known. It is assumed that ecology and bioclimatic variables are responding for such spatial distribution. But these factors are not fully understood. A tool for linking climatic factors with presence/absence of any species has been devised by Phillips et al., 2004 [24] and Yang et al., 2013 [25], based on MaxEnt entropy algorithm [24] can link as well as predict the distribution in any geographic area. It is also known as ecological niche modelling and well established algorithm to identify the potential suitability of different epidemic diseases, vectors, and fauna and flora species [26-30]. The risk assessments and prediction of host and vectors using MaxEnt algorithm have been investigated in other vector borne diseases like malaria, Leishmaniasis, Rift Valley fever virus, dengue, and West Nile virus, and Japanese encephalitis [31-35]. The results of species distribution model can help improve tick monitoring, surveillance and provide guidance for implementing control programmes [31, 36, 37].

It was thought prudent to understand the bioclimatic factors responsible for present distribution as well as the potential distribution of *Haemaphysalis spinigera* in India. Therefore, the present study used the ecological niche modelling (MaxEnt) approach to determine the risk areas of KFD and climatic sensitivity of *Haemaphysalis spinigera* for southern India, on the basis of field survey and existing occurrence data. In addition, our modelling results took into explanation the link between model-based favourable climatic conditions and the possibility of monkey death as well as KFD tick expansion in the endemic and potential areas in other parts of India. It is only efficient strategy for controlling and preventing the disease is to find out the biological and climatic risk of *Haemaphysalis spinigera* as well as KFD.

## 2. Materials And Methods:

### 2.1.1 *Haemaphysalis spinigera* tick occurrence data:

Data on reported availability of *Haemaphysalis spinigera* were collated by systematic and comprehensive literature retrieval from the google scholar, Cochrane library, PubMed and the web of science database, by using the keywords Kyasanur Forest Disease, *Haemaphysalis spinigera* occurrence, monkey death by KFD virus, KFD in India, human cases of KFD (**Additional file 1**). The literature dealing with availability of *Haemaphysalis spinigera*, occurrence of KFD cases or monkey death from 1957 onwards were taken into consideration to ascertain the coordinates. Location of confirmed cases (human cases and monkey death) were converted into point features (exact latitude and longitude, 1 km × 1 km) or polygon features (i.e., localities, villages, districts) geo-referenced using Google Earth and Arc-GIS for the rectification of latitude and longitude [38]. When the name of the locality or village could not be identified at the administrative level, the coordinates were overlaid in a geographic information system (GIS) and assigned to the appropriate polygon feature [38]. All the locations of the occurrence of *Haemaphysalis spinigera* tick were transformed into WGS 84 datum using Arc-GIS software. Since the present study was conducted by the resolution of 30 arc-second (approximately 1 km × 1 km resolution), localities within one pixel were selected as one occurrence point. Altogether, 34 locations with confirmed human cases, monkey deaths or availability of *Haemaphysalis spinigera* ticks were georeferenced from all the reported areas of Karnataka, Maharashtra, Kerala, Goa, and Tamil Nadu (**Fig 1**) (**additional Table 1**).

### 2.1.2 Bio-climatic variables:

Bio-climatic variables are biologically more significant to identify the physio-ecological resistance of plants and animals than simple temperature and rainfall [39, 40]. Therefore, these variables are commonly used in bio-climate envelope modelling [31, 41]. The study used 19 bio-climatic variables as potential predictors of *Haemaphysalis spinigera* distribution (as shown in **additional Table 2**). Raster-based bio-climatic variables were collected from the WorldClim Version2. The spatial resolution of these bio-climatic layers is ~1 km (30 arc seconds) and show extremity and seasonality of temperature, annual trends of precipitation and temperature parameters.

Of nineteen bio-climatic variables, five extremely correlated variables, having negligible effect on the model, were removed to reduce the masking effect and produce a model with better predictability [42]. The test was run by Pearson's correlation coefficient ( $r$ ) using ENM Tool (version 1.3), and a cross-correlation ' $r$ ' values of more than 0.80 was taken as a cut of threshold [25, 42] (**additional Table 3**). Finally, for modelling, the remaining 14 bio-climatic variables having a higher permutation significance and percent contribution were used. Based on the MaxEnt produced response curves, the relationship between bioclimatic variables and habitat suitability for *Haemaphysalis spinigera* occurrence were evaluated.

### 2.2 Predictive modelling:

The ArcGIS 10.3 and ENVI 5.1 softwares were used to generate raster-based spatial layers of the bio-climatic variables. The maximum entropy (MaxEnt) modelling is a machine learning algorithm [24] that calculates the probability distribution for a vector or species location based on different environmental restraints. The model executes well even with less number of sampling points than other machine

learning methods [43]. It uses presence-only vector/species location point to predict the potential distribution based on MaxEnt theory [24]. The basic principle of this algorithm is to ensure that approximation meets any limitations on the unknown points, meaning that the calculated probability of unknown distribution represents less number of constraints with a set of extra choices [44, 45]. However, in this study we used 34 locations' data about the presence of *Haemaphysalis spinigera* and generated pseudo-absences. About 10,000 background points were randomly selected by the maximum entropy algorithm. Data on the presence of ticks were divided into 75% random samples to calibrate the model, and the 25% random samples were utilized to assess the model performance. We used subsampling method in an attempt to create a stable model because it has advantages over bootstrap and cross-validation [46, 47], and 50 replicates were chosen to run the model.

The model also suggests settings to assess complexity of the model by altering regularization multipliers and feature classes. Sixteen different combinations of the feature classes were created to identify the appropriate feature, by retaining the linear function in each feature, which was then used for model performance. In order to balance the fit of the model and to avoid overfitting, regularization multipliers were used [48]. The selected default value for model calibration is 1.0. In total, 123 models combinations were created for selecting the best fit model in different settings. Other values of the model were set as default to get better results.

### **2.3 Threshold identification:**

For model results indicating probability of presence (suitability of a species), the logistic value ranging from 0 (unsuitable) to 1 (max. probability of presence) was used [24]. By applying 'max SSS' (maximum test sensitivity with specificity) logistic threshold value, binary unsuitable/maximum suitable map has been prepared. Specificity (Sp) and Sensitivity (Se), which are independent, implies the likelihood of a model that adequately forecasts a species absence and presence in any location and measures the commission and omission errors. Sp and Se are distinct and not influenced by predominant across models [49]. In the ROC curve, the 'max SSS' identifies a point in which the tangent slope is 1 that demonstrates 1-specificity and sensitivity for maximizing TSS value. The value can be utilized as an efficient threshold value when only occurrence or target species presence data are available and has been used extensively [50-52]. This binary raster was used to show the potential distribution of the *Haemaphysalis spinigera* ticks using SDM toolbox 2.0. The selection of backgrounds for latitudinal changes resulting from the geographical coordinate systems has been corrected by a bias file [53].

### **2.4 Model assessment and validation:**

To estimate the goodness of fit of the model, the Area Under the receiver operating characteristics Curve (AUC) was used, and the highest value indicated as the best performer. The AUC is a threshold-independent technique of a model assessment to discriminate outcomes of presence/absence [54]. AUC values vary from least value 0 to the highest value 1. The 0.5 value signifies that the model findings were less than random, while the 1.0 value indicates complete discrimination [54, 55]. In the Jackknife test, the

contribution of the bio-climatic factors was also measured. The detailed methodological flow diagram in this work are shown in [Fig 2](#).

### 3. Results:

#### 3.1 Model performance:

The logistic results for the presence of tick suitability and distribution of Kyasanur forest disease was found highly significant, where AUC results for the training sample is 0.898 and for the test sample is 0.859 (**Fig 3**). This suggests that the bio-climatic variables set, used for the prediction model, and interpreted the predicted potential suitability very well with very high accuracy. The optimum threshold value, which provides equal weight to specificity and sensitivity, was selected to classify suitable areas of *Haemaphysalis spinigera*.

#### 3.2 Identified bio-climatic variables for distribution of *Haemaphysalis spinigera*:

Of fourteen bio-climatic variables used for modelling, more influential variables affecting the spatial distribution of *Haemaphysalis spinigera* were the average temperature of the warmest quarter (bio10, contributed 32.5%), average diurnal temperature range (bio2, contributed 21%), precipitation of wettest period (bio13, contributed 17.6%), and annual precipitation (bio12, contributed 11.1%). The cumulative contribution of these variables was 82.2%. The variable having high permutation importance was the average temperature of the warmest quarter (40.1%). The remaining 12 variables, i.e., annual mean temperature (Bio1), average temperature of the driest quarter (Bio9), average temperature of the coldest quarter (Bio11), rainfall of the warmest quarter (Bio18), mean temperature of the wettest quarter (Bio8), precipitation of wettest quarter (Bio16), rainfall of driest quarter (Bio17), precipitation of driest period (Bio14), and precipitation seasonality (Bio15) contributed 17.8% altogether to the suitability model (**table 1**). Therefore, the average temperature of warmest quarter and mean diurnal temperature change are very significant variables contributing to the risk area mapping of KFD. Both variables generate the best prediction results when used individually from Jackknife analysis. **Figure 4** shows the jackknife test results of the climatic variable importance as estimated by the model.

#### 3.3 Association of *Haemaphysalis spinigera* tick to climatic variables:

The **Figure 5a-n** indicates individual response curves of the association between each bio-climatic variables and the possibility of *Haemaphysalis spinigera* tick presence as estimated by the model. The response curves from the performance of the model show the differences in the logistic value conveyed by alteration in each parameter if the mean value of all other variables preserved. However, there is an overall non-linear negative relationship detected for the annual average temperature (Bio1), average temperature of the warmest quarter (Bio10), average temperature of the driest quarter (Bio9), and mean temperature of the wettest quarter (Bio8) indicating that higher the temperature intensity, the lower would be the *Haemaphysalis spinigera* tick distribution. *Haemaphysalis spinigera* tick preferred habitat having an annual mean temperature (bio1) between 23-26.2°C, mean temperature of the driest quarter (bio9)

between 20-28°C, and mean temperature of the wettest quarter (bio8) between 22.5-25°C. Precipitation of the wettest period and Annual precipitation showed a non-linear positive response, indicating that higher the precipitation intensity, the higher would be the *Haemaphysalis spinigera* tick distribution. The mean temperature of the warmest quarter (bio10) represented the temperature in the warmest season and revealed a significant probability of *Haemaphysalis spinigera* presence between 25.4-30°C. The mean diurnal temperature range is the difference between daily maximum and daily minimum temperature, and it revealed a very high probability of tick presence between 8-10°C. The response to precipitation of the wettest period (bio13) showed that precipitation of 500-650mm highly favoured the presence of *Haemaphysalis spinigera* tick. The other optimum bio-climatic parameters for *Haemaphysalis spinigera* tick suitability are shown in **table 1**. Subsequently, the high tick population could be a cause for monkey death, as well as the human case.

### 3.3 Potential risk areas of *Haemaphysalis spinigera*:

We converted the predicted probability map of *Haemaphysalis spinigera* tick suitability from the MaxEnt model to presence and absence using 'max SSS' logistic threshold value. The predicted presence areas were classified as very high to moderately suitable areas, and the absence areas were classified as non-suitable areas for *Haemaphysalis spinigera*. Based on the proportion of bioclimatic suitability areas, the potential suitability map was classified into five different suitability categories, i.e., 'very high suitability' (0.80 - 1.0), 'high suitability' (0.79 - 0.60), 'moderate suitability' (0.59 - 0.40), 'low suitability' (0.39 - 0.20), and 'very low suitable' class (0- 0.19). The predicted potential areas of *Haemaphysalis spinigera* under present bio-climatic settings are shown in **Fig 6**. As per results, about 26,429 km<sup>2</sup> (4%) area comes under 'very high potential' for *Haemaphysalis spinigera*, followed by 'high potential' at 18,258 (3%) and 'moderate potential' at 45,759 km<sup>2</sup> (7%) (**table 2**). The results further show that Karnataka is the most potential region, followed by Maharashtra, Kerala, Goa, and Tamil Nadu. The high to very high suitable areas are Shivamogga, Chamrajnagar, Chikmagalur in Karnataka; Kozhikode and Wayanad districts in Kerala; Raigad, Ratnagiri districts in Maharashtra; Nilgiris district in Tamil Nadu; North Goa district in Goa, requiring continuous vigilance (**Fig 6**). The district-wise suitability map shows linear spatial clustering along the Western Ghats as a very high-risk zone of the potential distribution of *Haemaphysalis spinigera* distribution. In those districts, extensive survey, continuous vigilance is required, especially from November to March when most KFD cases occur. The percentage of the risk area in each state is shown in **table 3**.

## 4. Discussion:

This is the first study to link the bioclimatic variables with the potential distribution of *Haemaphysalis spinigera* tick in South India. Based on tick occurrence records, MaxEnt modelled the potential distribution of *Haemaphysalis spinigera* tick as 23,265 sq. km (58.66%) spread over the Shivamogga, Chamrajnagar, and Chikmagalur districts in Karnataka; 4,765 sq. km (12.02%) in Kozhikode and Wayanad districts of Kerala; 7198 sq. km (18.15%) in Raigad, Ratnagiri districts of Maharashtra; the Nilgiris districts in Tamil Nadu; North Goa district in Goa (**Fig 6**). Most of the areas in Karnataka as well as southern India are

suitable for KFD in present climatic conditions. The predicted risk areas show an expanding distribution in hot and drier climatic conditions.

The relationship between the growing distribution of *Haemaphysalis spinigera* tick and variations in the mean temperature of warmest quarter (bio10) and mean diurnal temperature range (bio2) means dry and warmer climatic conditions were evident in the model results [16-18]. The risk areas of *Haemaphysalis spinigera* tick were more intense in the locations with precipitation of wettest period 500-650mm, mean diurnal temperature range 8-10°C and mean temperature of the warmest quarter 25.4-30°C. The climatic requirements indicate KFD's transmission occurs during the non-rainy season as the nymphs of *Haemaphysalis spinigera* ticks are active during this season **(Fig 2)**.

*Haemaphysalis spinigera* ticks are most sensitive to deforestation [8, 15]. The expansion in areas of the tick population in Africa was found related variations in temperature and precipitation [56]. Moreover, the warmer temperature has been found as the most influential factor for the geographic range shifting of some tick species [57, 58].

In Karnataka, Goa, Maharashtra, Kerala, Tamil Nadu the increasing distribution of *Haemaphysalis spinigera* tick was mostly seen in the deciduous, and neighbouring semi-evergreen and evergreen areas [59] **(Fig 1)**. Studies showed that these forested lands were more prone to dry climate with decreasing precipitation [60]. The decrease in precipitation during the pre-monsoon (southwest) resulted in short-term meteorological droughts in this region [61, 62] which increases the suitable areas of *Haemaphysalis spinigera* tick. Secondly reported areas of KFD, the annual rainfall was relatively lower and temperature relatively higher than the other areas of Western Ghats but can be considered as the risk areas of *Haemaphysalis spinigera* tick, according to Raj and Azeez (2010) [63], and Nair et al., (2013) [64] the aridity index increases significantly in this region. In case of ticks populations get exposed when the mean temperature of the warmest quarter ranges between 25.4-30°C, and more than 30°C is not suitable, and even ticks die because of water loss due to destruction in the integument. Moreover, the endemic areas of KFD in Shivamogga district are also shifting from Shivamogga to Thirthahalli, Hosangara taluka, which are presently the most endemic region in Shivamogga district **(Fig 7)**. According to bioclimatic data, suitable diurnal temperature range and mean warmest month temperature with low precipitation were found in the above mentioned talukas than the other endemic areas of Shivamogga taluka, which can explain the reason for the high endemicity of KFD **(Fig 2)**.

Accordingly, our results also indicate a momentous growth in *Haemaphysalis spinigera* distribution or risk areas of KFD with favorable climatic conditions (warmest month temperature and diurnal temperature range) in seven areas namely Shivamogga, Chamarajanagar, Bandipur National Park, Madurai Tiger Reserve, Wayanad, Sattari, Malappuram, where the highest number of monkey death and human cases were observed. Moreover, the influence of climatic factors may be having an important bearing on monkey death in Shivamogga which need further study.

Species distribution modelling known as 'habitat suitability', 'ecological niche', and 'potential distribution' modeling and these are used to predict the suitable habitats [65] of a tick species. In this study, we limited

the increasing distribution of *Haemaphysalis spinigera* tick potentiality in terms of climatic variables so as to identify the climatic determinants in the habitat alteration in southern India. As the ticks' distribution is associated with deciduous, evergreen, and semi-evergreen forest [59], we omitted land use and land cover variables. Soil characteristics were also excluded from this study since the high resolution, and more accurate data were not available. Moreover, we also excluded the role of host-agent-environment factors due to the lack of proper information over this region. Regardless, further spread of *Haemaphysalis spinigera* tick may be affected by climate change, emphasizing the need for further studies.

## 5. Conclusion:

Bio-climate envelop modelling approach has been found a very useful tool to link bioclimatic variables with present and predicted distribution of Kyasanur Forest Disease. It has predicted the potential climatic suitability of KFD in Shivamogga, Chamrajnagar, Chikmagalur in Karnataka; Kozhikode and Wayanad districts in Kerala; Raigad, Ratnagiri districts in Maharashtra; the Nilgiris district in Tamil Nadu; North Goa district in Goa. These districts are categorized as dry and hot climate than other districts of the Western Ghats. The predicted potential risk mapping results emphasized the significance of climatic variables in identifying the potential risk district for KFD warranting surveillance for KFD. Future study should be designed incorporating further risk variables (i.e. monkey dispersal pattern, seasonal forest characteristics), and other host-agent-environment factors in Shivamogga district as well as in southern states of India.

## Declarations

**Availability of Data and Materials:** Relevant data are within the manuscript and are freely available.

**Author Contributions:** M.P.-data collection, data processing, model development, and drafting of manuscript. P.S.-data collection and drafting of manuscript, R.C.D.-Conception, analysis, drafting and critical revision of manuscript, All authors read and approved the final manuscript.

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**Conflict of Interest:** We have no conflict of interest of any matter regarding manuscript, figures and tables that submitted in your journal, all of submitted file is prepared by the authors.

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## Tables

Table 1: Selected set of bio-climatic variables after PCA results and their contribution to the KFD suitability.

Id of bioclimatic variable	Selected bio-climatic variable	Contribution (%)	Optimum bio-climatic conditions
Bio1	Annual mean temperature	0.1	23-26.2°C
Bio2	Mean diurnal temperature range	21	8-10°C
Bio8	Mean temperature of wettest quarter	2.4	22.5-25°C
Bio9	Mean temperature of driest quarter	0.5	20-28°C
Bio10	Mean temperature of warmest quarter	32.5	25.4-30°C
Bio11	Mean temperature of coldest quarter	3.9	16.5°-24C
Bio12	Annual precipitation	11.1	>1400 mm
Bio13	Precipitation of wettest period	17.6	500-650 mm

Table 2: Area under different risk classes for KFD tick

Risk categories	Area (sq. km)	Area in %
Very low risk	359767	53
Low risk	220650	33
Medium risk	45769	7
High risk	18258	3
Very high risk	26429	4
Total	670873	100

Table 3: State-wise high risk area for KFD tick

States	High suitable area (km <sup>2</sup> )	% of very highly suitable area in the total suitability	% of very highly suitable area in the state
Goa	2056	5.18	55.66
Karnataka	23265	58.66	12.16
Kerala	4765	12.02	12.64
Maharashtra	7198	18.15	2.34
Tamil Nadu	2376	5.99	1.82
Total area	39660	100	

## Figures

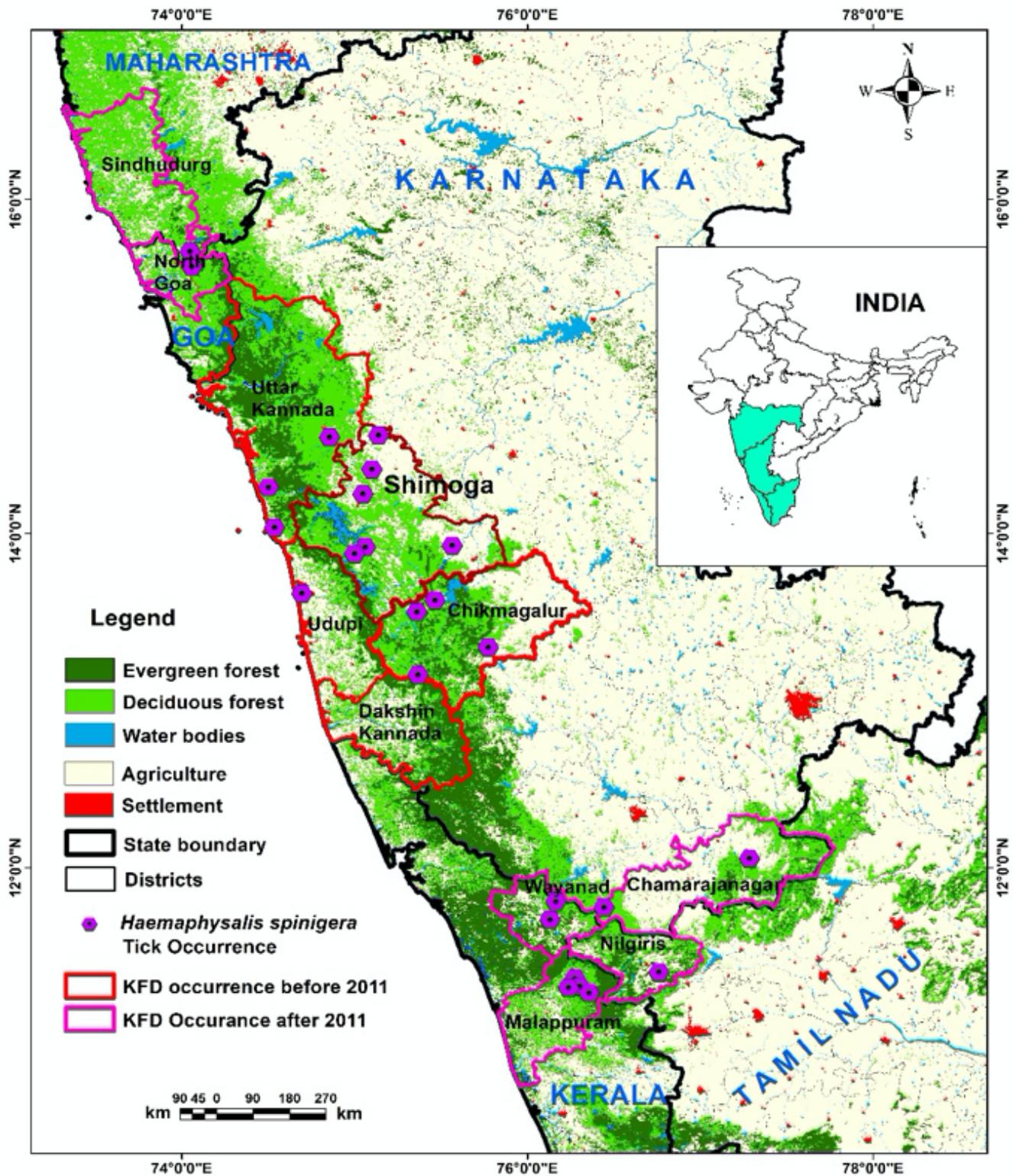


Figure 1

Locations of reported distribution of *Haemaphysalis spinigera* tick, KFD endemic areas till 2011 and afterwards.

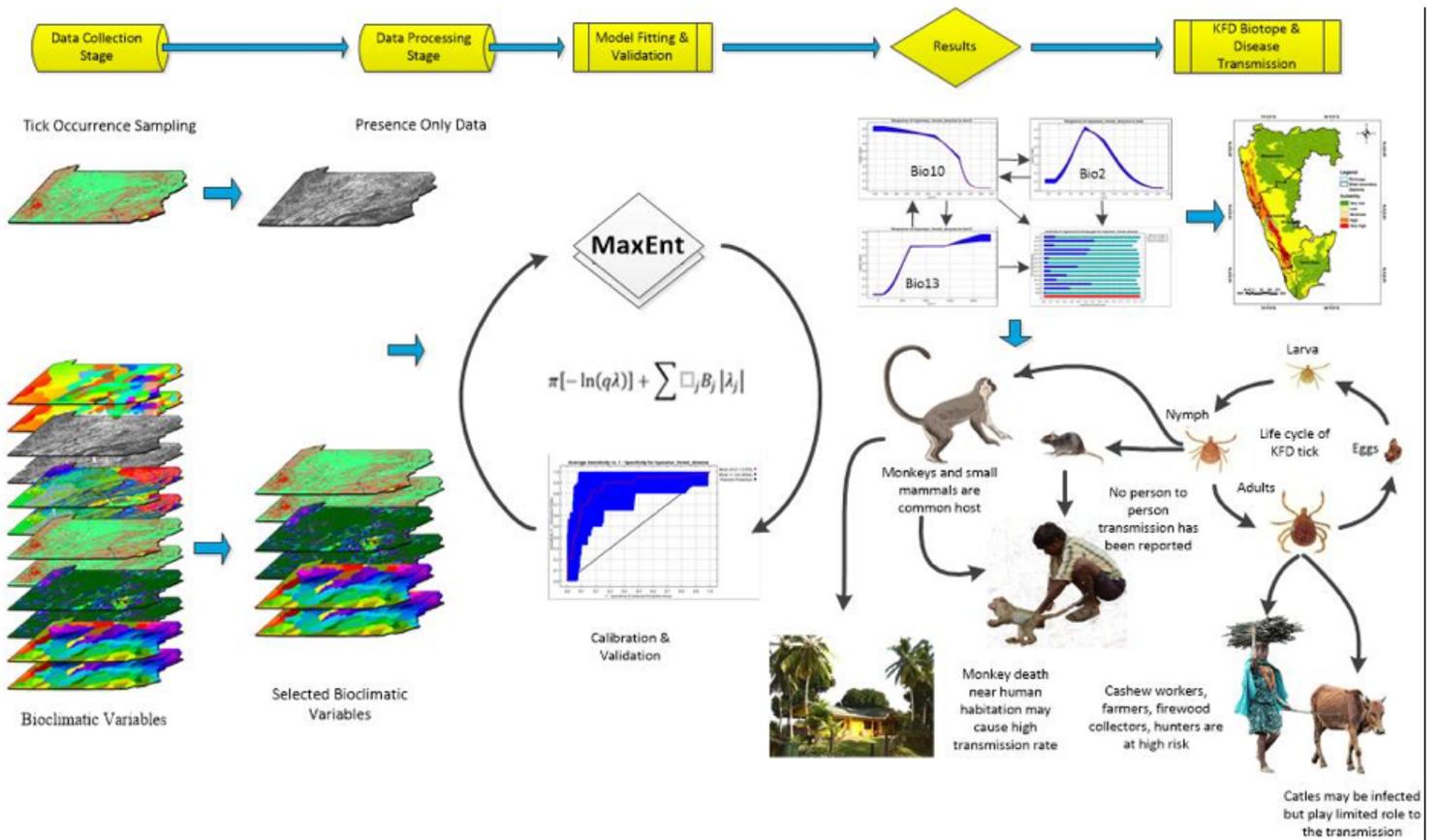
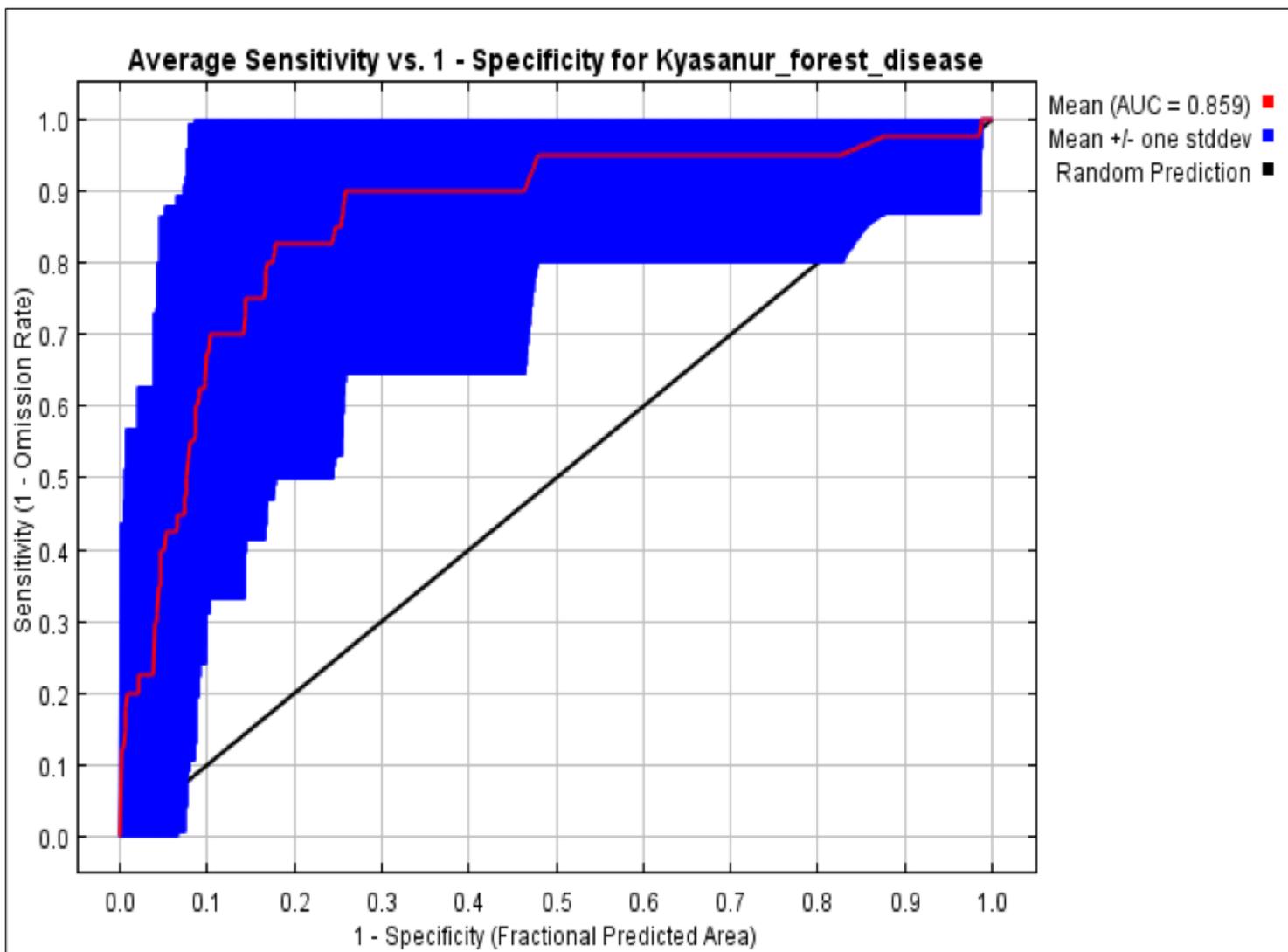


Figure 2

Methodological flow diagram showing the link between suitable climatic conditions and disease transmission of Kyasanur Forest Disease.



**Figure 3**

The ROC curve for *Haemaphysalis spinigera* tick showing different AUC values.

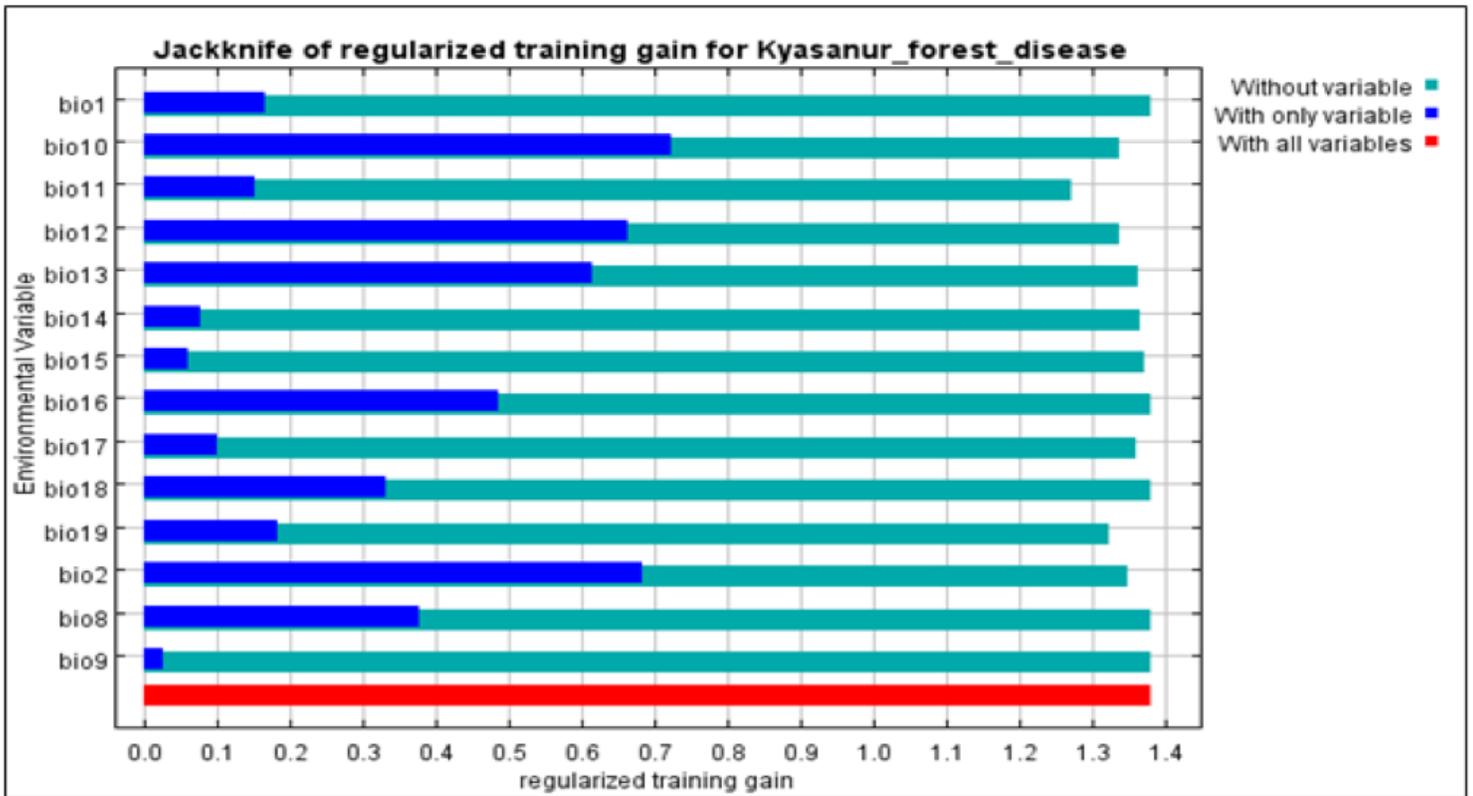


Figure 4

The Jackknife test results indicating the relative importance of bio-climatic variables.

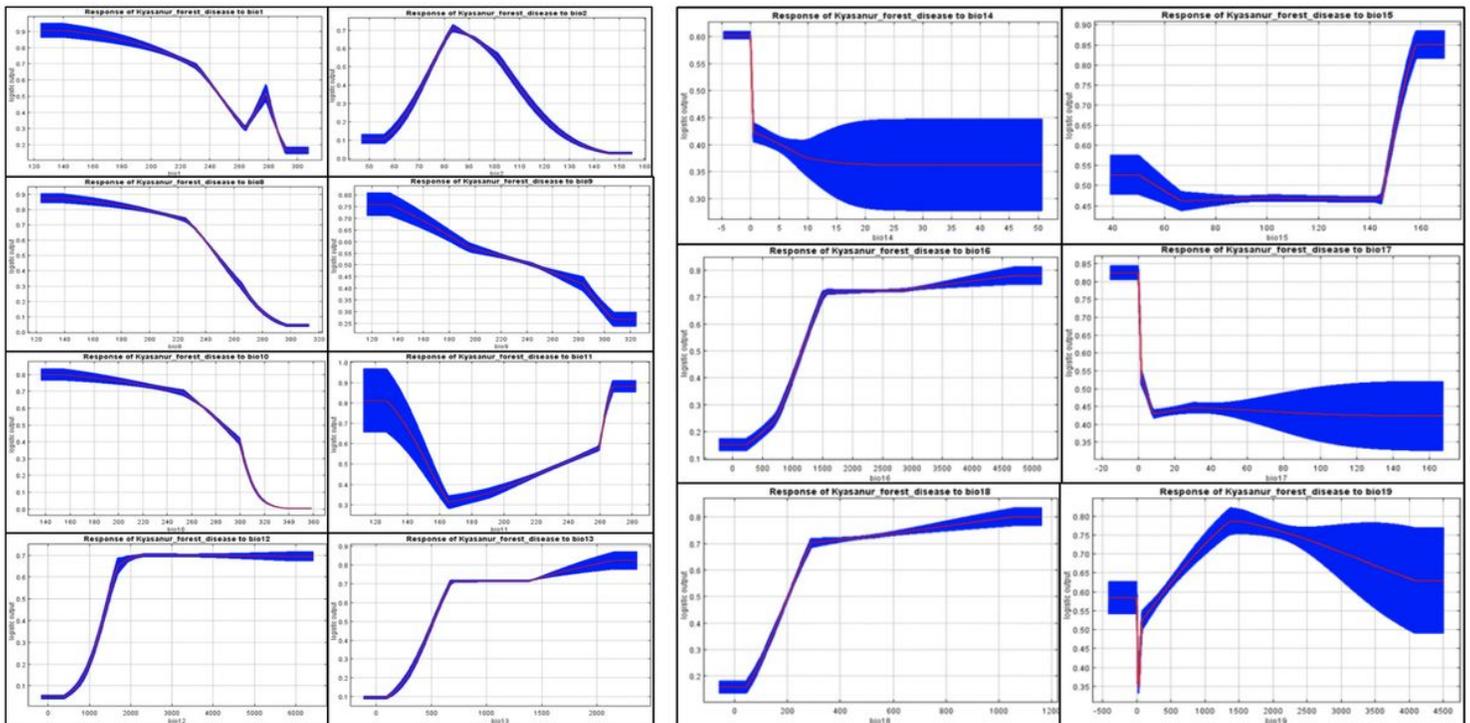


Figure 5

Relationship between selected climatic variables and probability of the presence of *Haemaphysalis spinigera* ticks. (a) annual mean temperature (Bio1, °C), (b) mean diurnal temperature range (Bio2, °C), (c) mean temperature of wettest quarter (Bio8, °C), (d) mean temperature of driest quarter (Bio9, mm), (e) mean temperature of warmest quarter (Bio10, mm), (f) mean temperature of coldest quarter (Bio11, CV), (g) annual precipitation (Bio12, mm), (h) precipitation of wettest period (Bio13, mm), (i) precipitation of driest month (Bio14, mm), (j) precipitation seasonality (Bio15, CV), (k) precipitation of wettest quarter (Bio16, mm), (l) precipitation of driest quarter (Bio17, mm), (m) precipitation of warmest quarter (Bio18, mm), (n) precipitation of coldest quarter (Bio19, mm). Red curves indicate the average response and blue margins signify  $\pm$ SD estimated over 50 replicates.

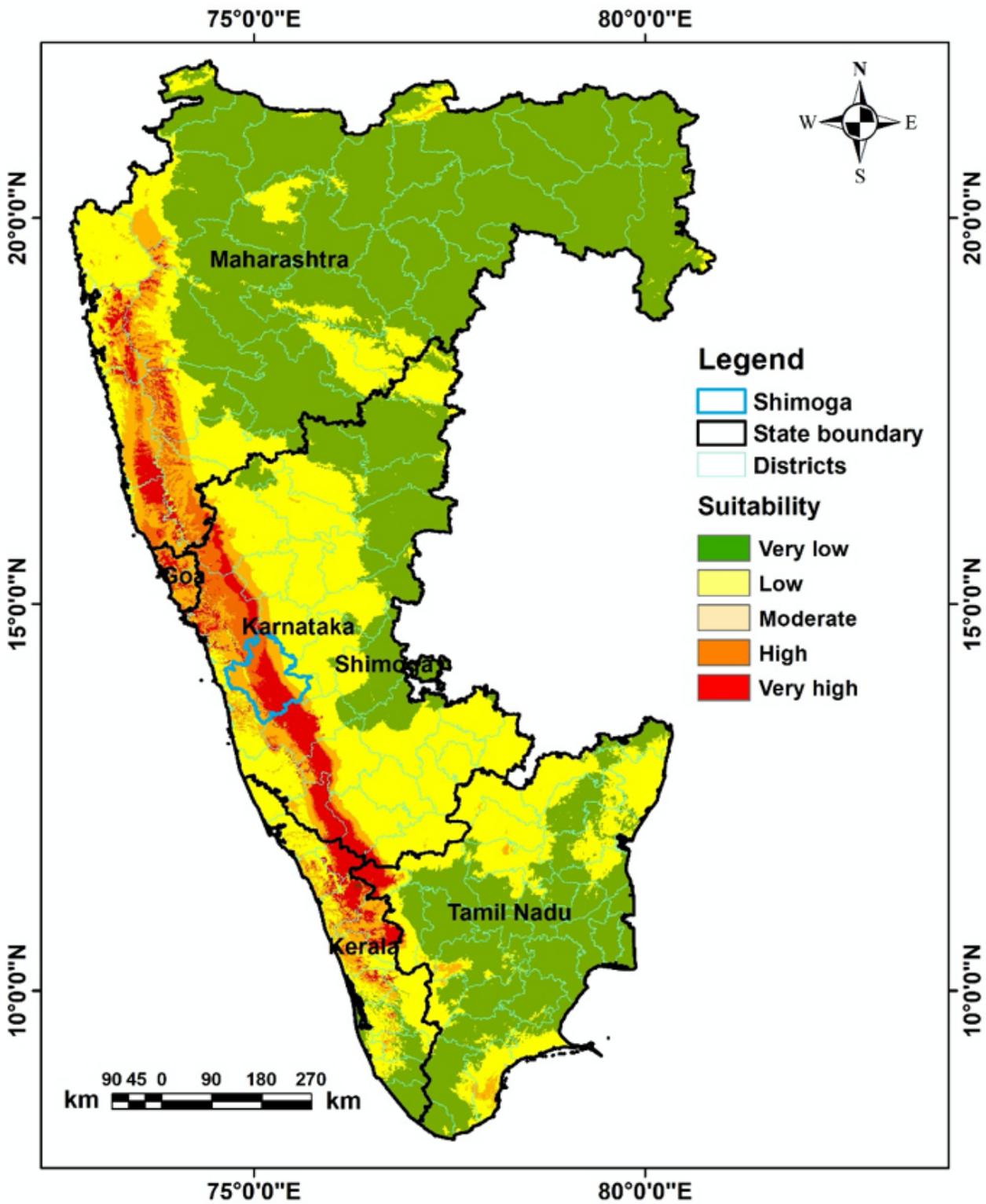


Figure 6

Map of the predicted potential distribution of *Haemaphysalis spinigera* tick.

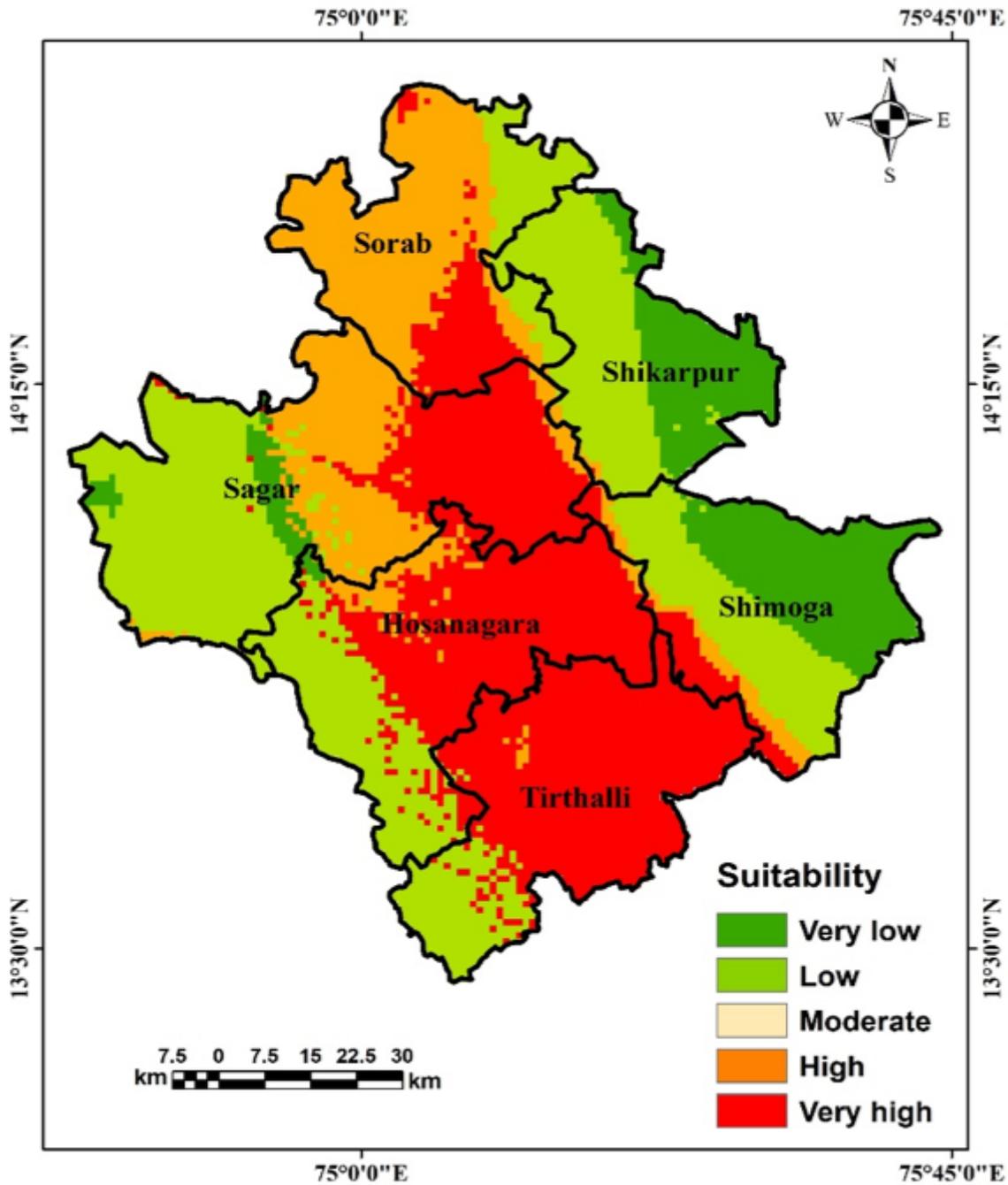


Figure 7

Predicted potential distribution of *Haemaphysalis spinigera* tick in endemic region of Shivamogga district.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Additionaltable.docx](#)