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Integration of Time into a 2-Dimensional Geography to Visualize Spatio-Temporal Clusters of Dog Rabies in Thailand

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ABSTRACT

Introduction: Space-time scanning analysis to detect cylindrical spatio-temporal clusters of diseases is available. Yet, there is no satisfactory way to visualize the data. Our aim is to visualize spatio-temporal cylindrical clusters of dog rabies in Thailand from 2005 to 2021.

Methods: We obtained dog rabies data from 2005 to 2021 from the World Animal Health Information System under the World Organisation for Animal Health (WOAH). The rsatscan package in R was applied to identify spatio-temporal clusters of dog rabies using the discrete Poisson model and Monte Carlo simulation. Using a user-defined function developed by our research team, cylindrical shapes were created based on the provincial administration maps to demonstrate significant clusters over space and time.

Results: The average incidence of dog rabies was 0.5 events per 100,000 human-years, and seven clusters were found during the study period in all five national regions, based on 15% of the population being at risk.

Conclusion: Our method to generate multi-dimensional graphics can comprehensibly visualize cylinder-shaped outcomes from spatio-temporal data. With the relatively large number of dog rabies clusters detected, more intensive control measures are required to alleviate dog rabies.

Key words: Spatio-temporal cluster; Rabies; Cylindrical visualization; R software; Thailand

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INTRODUCTION

Rabies is a global issue. Several countries, including Thailand, have collaborated to report animal rabies events to the World Organisation for Animal Health (WOAH).[1, 2] The animal rabies situation in Thailand, particularly in reservoirs such as dogs, has persisted for 30 years[3] and is a major public health threat.[3, 4]

Spatial analysis refers to an analytical technique to examine spatial dimensions associated with an outcome of interest, whereas temporal analysis refers to an analytical technique for investigating changes over time in an outcome of interest.[5, 6] Space-time scanning statistics is a technique in spatio-temporal analysis for detecting clusters that occur in both geographical (space) and chronological (time) dimensions, and also allows assessments of magnitude (e.g., relative risk) and significance.[7, 8] Space-time scanning detects disease clusters as cylindrical tubes that varies by geographic area and a height that varies by time.[9] The areas and periods of elevated risk inside a tube can be compared to outside the tube at baseline,[10, 11] each tube indicating a spatio-temporal disease cluster.[7] Space-time scanning can identify areas where the expected ratio of the event at the study period compared to the baseline is higher inside the area than outside the area,[12] known as the space-time cylinder clusters. The null hypothesis assumes that the observed cases are randomly distributed in space and time relative to the population at risk.[7]

Space-time scanning is suitable for small and compact cluster distribution patterns,[7] e.g., for outbreaks of hand-foot-mouth disease, West Nile virus in horses, and emerging clusters of COVID-19.[9, 10, 13] Space-time scanning of zoonotic diseases, particularly the distribution of infections in primary reservoirs, aids in naming target areas for effective disease prevention; for example, prevention of rabies in dogs is an effective way to preserve human life.[14, 15]

Data visualization with such a technique can yield additional insights that further contribute valuable data for relevant stakeholders. Several published articles have illustrated their spatio-temporal cluster findings on 2-dimensional administrative maps instead of 3-dimensional graphics,[16-22] Visualizing the result of spatio-temporal cluster analysis using cylindrical shape on a map can be a good alternative approach for public health planners.

Although previous studies have included spatio-temporal analyses of rabies data in Thailand,[3, 23, 24] they were based purely on spatial Bernoulli models, space-time permutation, and Bayesian spatial regression methods. There has not yet been an effective method to visually represent the longitudinal data at the country level derived from space-time analysis methods. We propose that the cylindrical cluster could be well visualized with a 3-D approach. Therefore, our study aims to describe and visualize spatio-temporal cylindrical clusters of rabies in dogs in Thailand for the time period between 2005 and 2021, when the data were available.

METHODS

Study setting

Thailand has predicted a dog population of 12.8 million[25] and a human population of 65 million.[26] The land is divided into five regions with 76 provinces: the North, Northeast, Central, East, and South as defined by the Thai government (Figure 1).

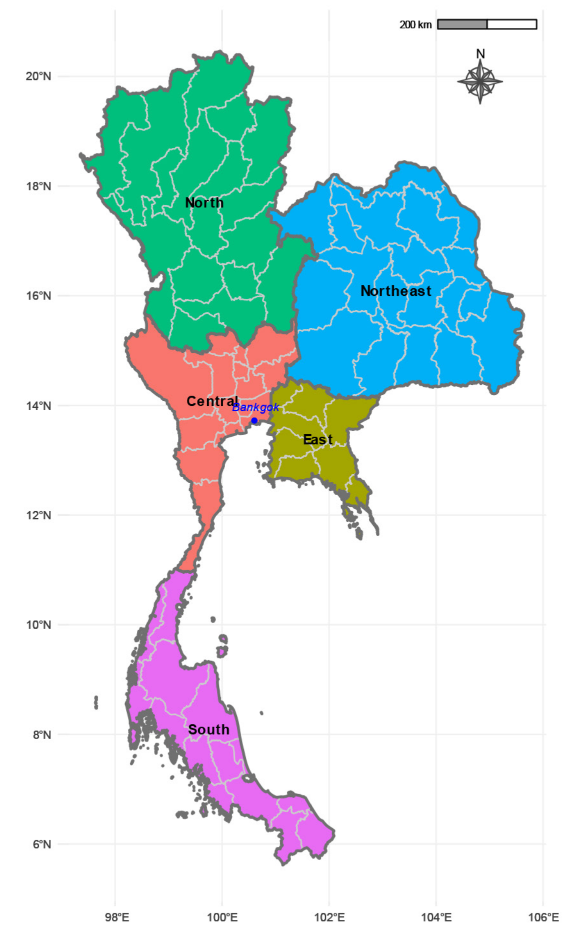

Figure 1. Thailand map with 76 provinces and 5 regions, namely, the North (green), Northeast (blue), Central (pink), East (yellow), and South (purple).

Study design

We conducted a secondary data analysis of longitudinal data on dog rabies. Figure 2 is an overview of the analysis workflow. The 76 province centroid were extracted from each of their polygon as the areas. The number of dog rabies cases was divided by the human population, with each province and year representing the incidence. The province centroids and rabies incidence divided by human population data were fed into rsatscan, a package in R software. The outputs, which are cylindrical parameters, were drawn for cylinder cluster visualization using a user-defined function

(Supplementary material 1) for cylinders (Figure 2).

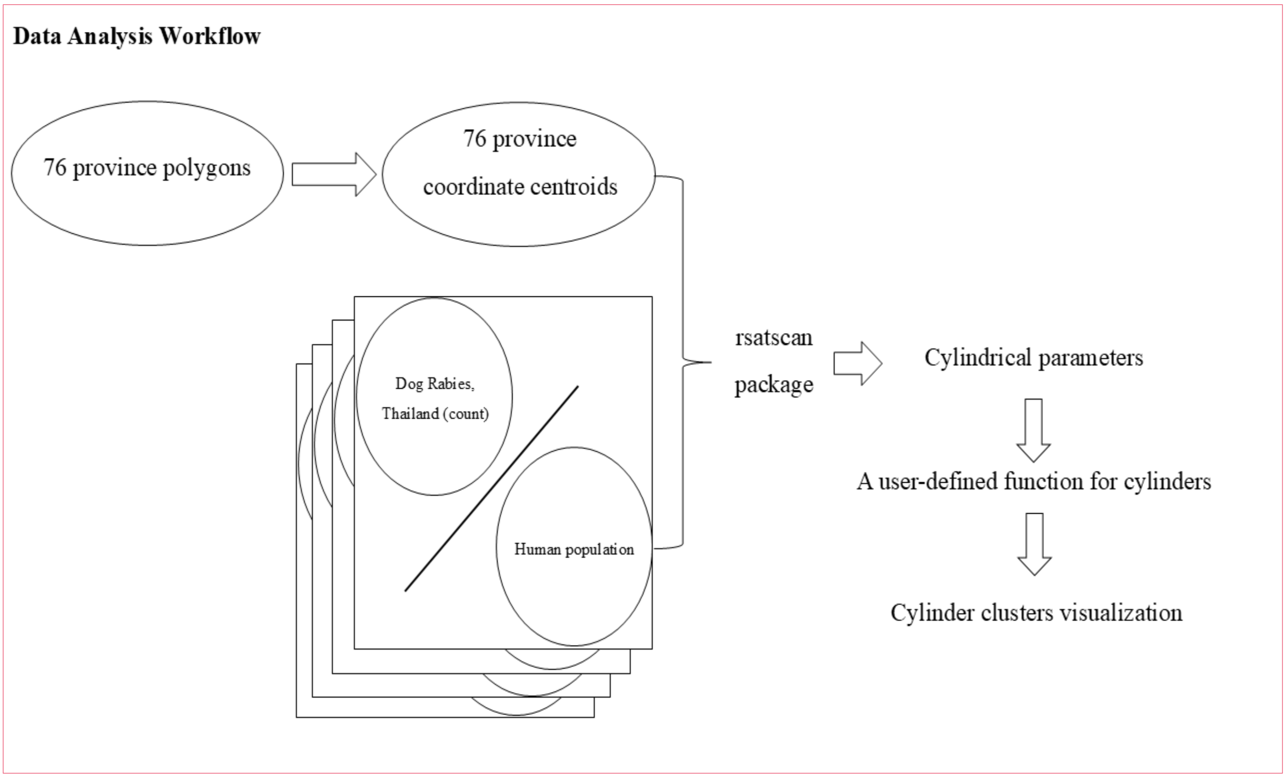

Figure 2. Data Analysis Workflow

Data sources

We downloaded data from the WOAH website (https://wahis.woah.org/#/dashboards/qd-dashboard)[27] with semester (later aggregated into the year), year, province, and total dog rabies cases classified by. We filtered the dataset on year (2005-2021), country (Thailand), disease (rabies virus (inf. with)), and species (dogs), and then exported the data as a Microsoft Excel worksheet.[1, 2]

We obtained human population data for each province during the study period from the Department of Public Administration, Thai Ministry of the Interior (https://stat.bora.dopa.go.th/stat/statnew/statyear/#/).[26] We retrieved polygons of the 76 provinces of Thailand in shapefile format from the Global Administrative Areas database (https://gadm.org/download_country.html).[28] All published datasets are shown in Table 1.

Data management

The semesters of dog rabies cases data was aggregated into yearly counts. The dog rabies count and human population were manipulated; for example, they were combined to calculate and display incidence across provinces and years. The centroids of the provinces were determined using the 'st_centroid' function from the sf package.[29] Data was also transformed to be in an appropriate format for the rsatscan package.[30] All processes were performed using the R version 4.4.2.[31]

Table 1. Variables, sources, accessed date, and variable units for the space-time scan analysis (All datasets were accessed on 7 February 2024)

Component	Source	Organization	Description (unit)
Count	https://wahis.woah.org/#/dashboards/qd-dashboard	WOAH*, †	Dog rabies cases reported in each province by year (dogs)
Population	https://stat.bora.dopa.go.th/stat/statnew/statyear/#/	DOPA**, Thailand	The human population in each province by year (people)
Location	https://gadm.org/download_country.html	GADM***	The dataset of polygons was calculated to get the centroids of each province (province)

* World Organisation for Animal Health founded as the Office International des Epizooties (OIE)
** Department of Provincial Administration, Ministry of Interior, Thailand
*** Database of Global Administrative Areas

Data analysis

Descriptive statistics

The 76 provinces of Thailand (for practical purposes, Beung Kan province, which didn't exist before 2011, was combined with Nong Khai province[32] for this analysis). We measure the yearly incidence by using number of dog rabies reported event as the numerator. Since it was not possible to get the total dog population and humans are at risk of must concern, we used number of human population (100,000) as the denominators. As infectious diseases expand exponentially, the visualized data must be log-transformed to allow enough details of the change of the low-incidence areas. We transform the value by taking log 10. For the province without any dog rabies in a population year, we add 1+ to all values before log transformation and get 0 on the log scale for the province without any event (log 1 = 0). Then, values were used to compute the graphics with the results. Disease trends over space and time were explored based on the five geographic regions of Thailand: North, Northeast, Central, East, and South. Plots were created using the ggplot2 package[33] (version 3.4.4).

Space-Time Scan analysis

The annual rabies rates for each province and coordinates of each centroid (Supplementary file 1), were analyzed using the rsatscan package.[30] A retrospective space-time scan analysis was performed using the discrete Poisson model and Monte Carlo simulation (999 iterations). The temporal window was set at 50% of the study period. Based on a previous similar study,[10] to have good incremental details, the spatial window was set at 50%, 20%, 15%, and 10% of the population at risk.

Tests for statistical significance and p-values were calculated through Monte Carlo simulation, replicating and comparing the rank of the maximum likelihood across the actual data with randomly generated data. To identify the most significant clusters, researchers looked at the ones with the highest likelihood ratio (LLR) values, as these clusters are less likely to occur by chance.[11] We considered the sets with statistically significant LLR values as secondary clusters.[9] The ratio of observed values within a cluster to expected values, compared to the baseline risk outside, is known as the relative risk.[11]

Visualization

Cylindrical clusters were visualized using a user-defined function in the shape package[34] (Supplementary file 1) developed by our research team. The parameters for these cylindrical clusters were derived from the information about the clusters' components obtained from the space-time scan analysis output. Table 2 provides a description of the specific parameters used for visualizing the cylindrical clusters, including the timeframe and segment.

The longitude and latitude points were plotted on the x-axis and y-axis, respectively, while the duration of disease clusters was displayed in the third-dimension by tilting the graphics window slightly.

Ethical considerations

Our study only involved the use of secondary data (aggregated data among humans and animals). The Animal Ethics Committee of Prince of Songkla University, Thailand, exempted our study from the ethical approval requirement (Ref.AG012/2024).

Table 2. Parameters for cylindrical cluster visualization

Component	Description	Unit
Coordinate	The centroid (latitude and longitude) of the centered province of significant disease clusters	degrees (°)
BEGIN_DATE	The first date of the study period was 1-January 2005	Day
START_DATE	The first day of the year the cluster started.	Day
END_DATE	The last day of the year the cluster ended.	Day
Timeframe	Periods of significant disease clusters ((END_DATE - START_DATE) / 365.2425)	Year
Segment	A vertical line representing the period from BEGIN_DATE to START_DATE	Year
Radius	The distance covering significant disease clusters from the coordinate parameter	Kilometers
Relative risk	The ratio of rabies risk within a window (cluster) divided by the risk outside the window.	By shading of grey

RESULTS

Demographic characteristics

Over the 17 years of the study period, 5238 dog rabies were reported from 71 of the 76 provinces. The average incidence of dog rabies at the country level was 0.434 events per 100,000 humans. The ranking average of dog rabies incidence in the five study regions is the East (0.872), Northeast (0.572), South (0.433), Central (0.384), and North (0.097), regions respectively. The top five provinces with the highest overall incidence per 100,000 humans were Yasothon (13.0), Amnat Charoen (11.4), Surin (11.3), Satun (10.9), and Mukdahan (9.65), all in the Northeast, except Satun, which is in the South region. Figures 3 and 4 visualize the incidence (number of events per 100,000 human population) in each year.

Figure 3 illustrates 2-Dimensions maps of Thailand divided into regions bordered by provinces, with shaded areas denoting the level of the incidence. Figure 4 uses a series of box plots to summarize the distribution of dog rabies by year and region. Each box summarizes the incidence of the provinces in the same region. From both figures, dog rabies incidences were relatively low in the North and Northeast regions and relatively high in the South and Central regions in the early years. From 2015, the incidence rose remarkably in lower parts of Northeast and South regions, followed by overall subsidizes in 2020 - 2021.

At the provincial level within the same region (Figure 3), the incidence varied remarkably. In the North region, there were notable disparities between Mae Hong Son and Chiang Mai Provinces. In the East, incidence rates were uniform throughout the study period. In the south, incidence rates were high in Songkhla, Satun, and Nakhon Si Thammarat provinces, whereas the far South provinces had persistently low incidence rates.

Visualizing spatio-temporal data in cylindrical projection on an administrative province map

Figures 3 and 4 are computer-intensive, and it is difficult to detect the spatio-temporal clusters. With the ‘rsatscan’ package and our own user-defined function, the results can be visualised more easily. The relevant geographical map is slightly tilted vertically to allow integration of the time perspective on the vertical axis. A spatio-temporal cluster is denoted by a cylinder appropriately positioned above the area where the cluster is located. The time dimension is visualized on the vertical axis, where the centroid of the cluster is located. The diameters of the ellipse reflect the geographic size of the cluster. The duration of the cluster denotes the time period where the cluster takes place. The shade of grey of the cylinder denotes the relative risk of dog rabies in the area compared to that outside. The internal part of each cylinder is made transparent to allow visualization of multiple cylinders.

The results of the space-time scan analysis using a 50% temporal window and various levels of populations at risk are detailed in Supplementary File 2. Scanning 50% of the population throughout the country geography, one cluster or outbreak was identified. The cluster occurred between 2016 and

2018, had a relative risk (RR) of 6.50, and covered an area of 180,541 km^2 involving 22 provinces in all regions except the South region.

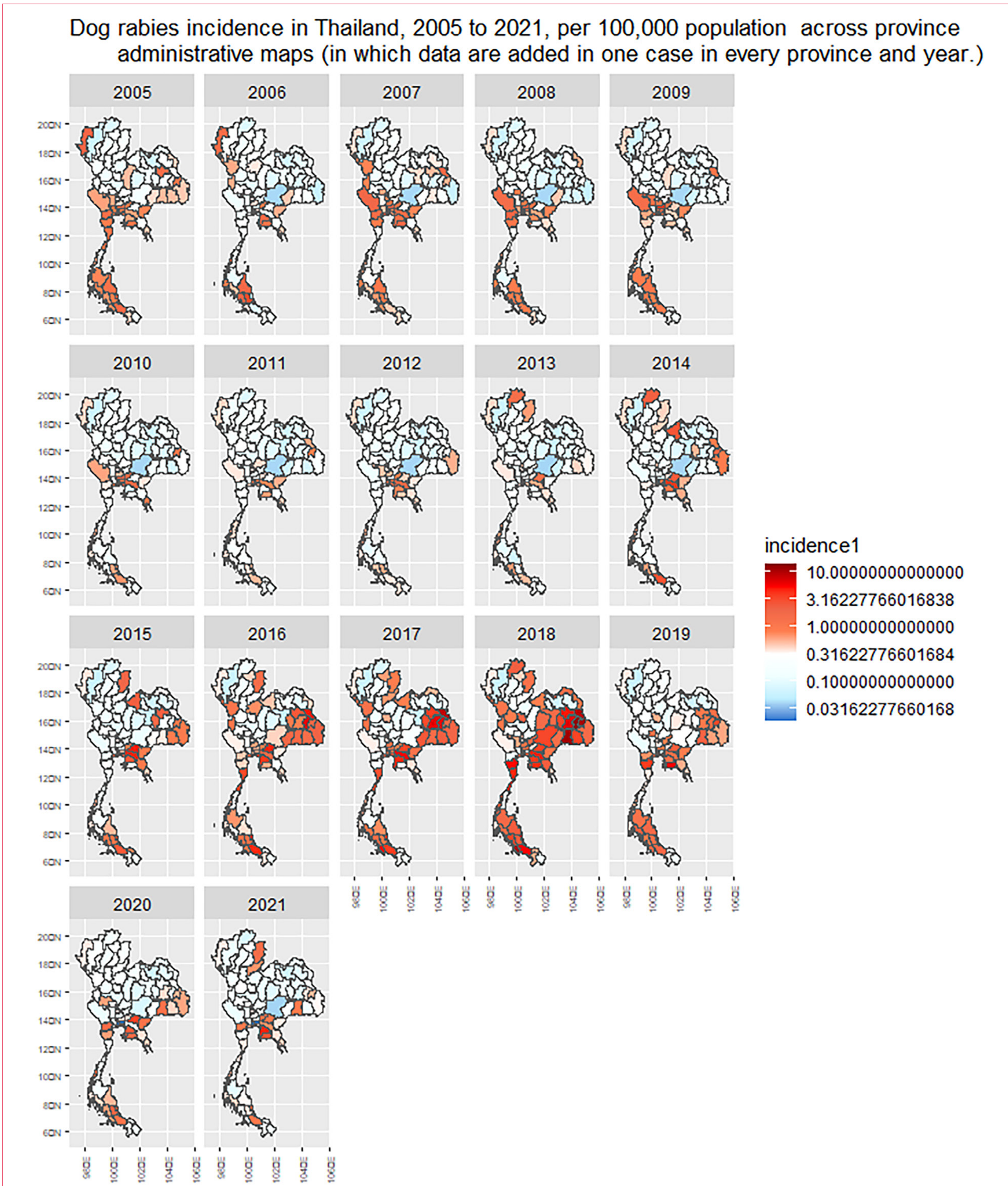

Figure 3. Dog rabies incidence in Thailand, 2005 to 2021, per 100,000 population across province administrative maps (in which data are added in one case in every province and year.)

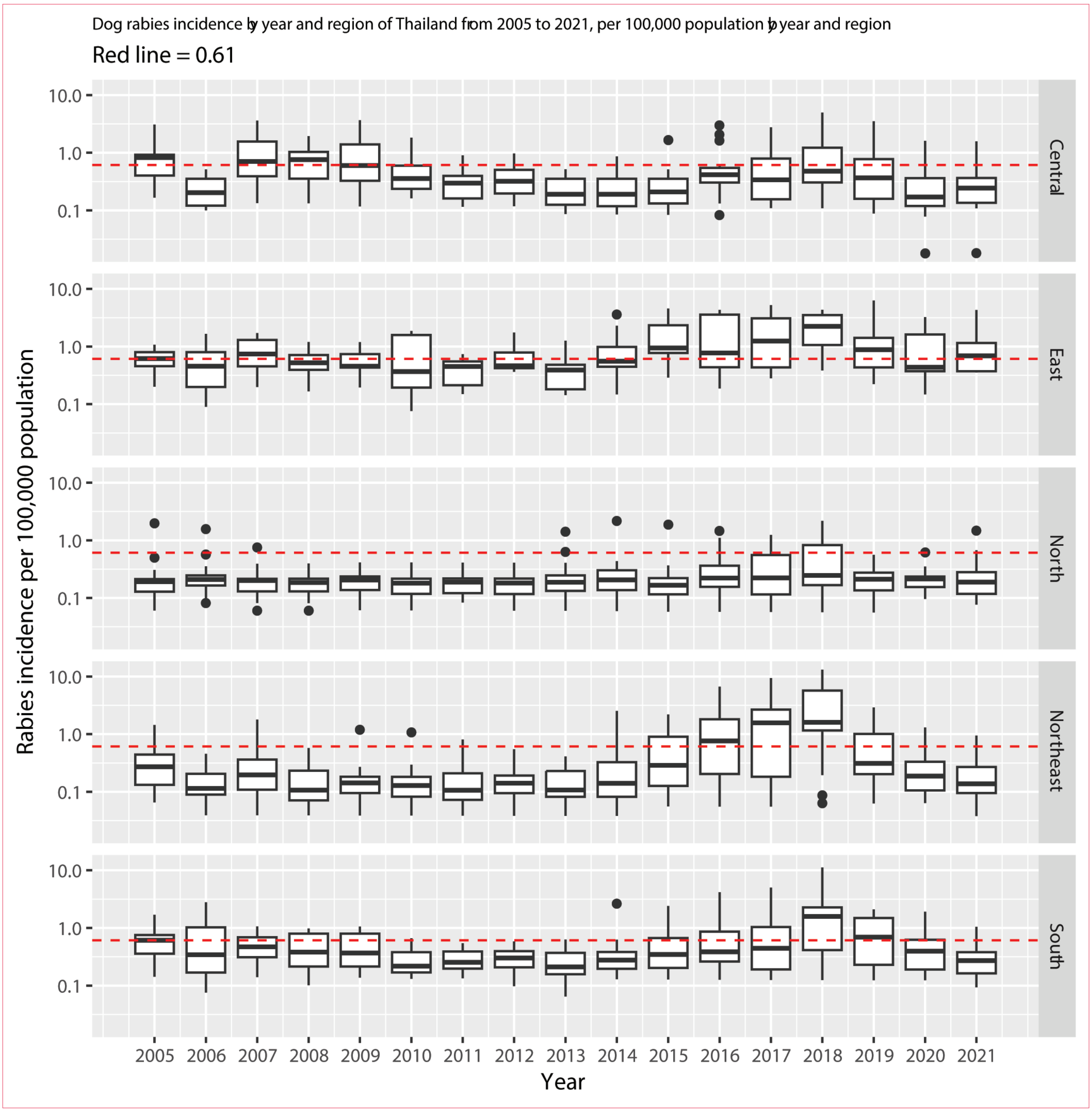

Figure 4. Dog rabies incidence by year and region of Thailand from 2005 to 2021, per 100,000 population by year and region (Red line = 0.61)

Using a dynamic scanning of 20% of the population across the country geography, five clusters were identified, covering four of the five regions with 37 provinces (Figure 5) and corresponded with the observed outbreaks in the region. The earliest cluster started in 2007 in six provinces and covered an area of 10,579 km2 of the Central region. The most recent, with only one year clustered, started in 2018 and covered an area of 82,616 km2 involving fourteen provinces in the Central, Northeast, and North regions. The relative risks for the two clusters were 2.37 and 2.48, respectively. The largest cluster or outbreak occurred in the Northeast and covered an area of 115,896 km2 from 2016 to 2018, with a relative risk of 8.84. The longest-lasting cluster occurred from 2014 to 2021 in the East region (RR=4.96). One short-lasting cluster emerged in a northern province with a relative risk of 3.58. There were no clusters in the South region.

Scanning 15% of population, seven clusters covering all five regions were detected. The first cluster began in the Central region in 2007 over a small area (2,792 km2), with a relative risk of 2.51. Clusters 2 to 5 started in similar periods between 2013 and 2014 in the North, Northeast, South, and East. The largest cluster that covered an area of 139,655 km2 was centered at Ubon Ratchathani in the Northeast, with a relative risk of 9.40 between 2016 and 2018. The longest-lasting cluster occurred in the East and lasted eight years (2014-2021), with a relative risk of 4.96. A cluster in the South, with a radius of 62.49 km, had a relative risk of 7.17 and lasted for six years (2014-2019). From 2018 to 2019, the two-year cluster in the Central region with a relative risk of 3.18 appeared. Then, scanning 10% of the population, eleven clusters were identified and dispersed throughout 37 provinces of the country. Nine of the clusters had relative risks ranging from 2.47 to 4.96. Around half of the identified clusters covered only one or two provinces. Dog rabies clusters resulted in populations at risk of 50%, 20%, 15%, and 10%, which are visualized in Supplementary Material File 3-6.

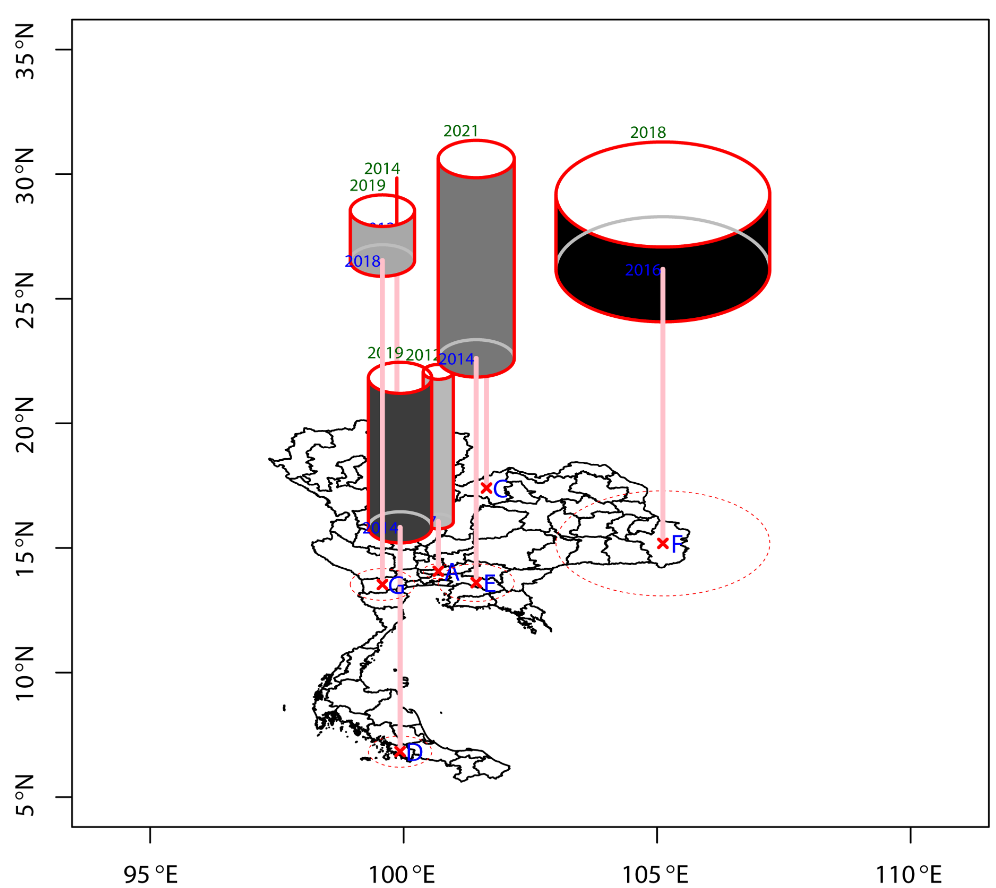

Figure 5. Spatio-temporal clusters of dog rabies in Thailand during 2005-2021, using a 50% temporal window and 20% of the population at risk

DISCUSSION

Between 2016 and 2018, dog rabies was reported in almost every province nationwide, marking the worst outbreak in the study period, according to both conventional 2-D and the new 3-D visualization method. With a setting at 15% of the population at risk, seven clusters were identified. Most clusters started in 2013 or 2014. The largest cluster and the cluster with the highest incidence occurred in the Northeast, while the longest-lasting cluster occurred in the East.

The largest expansion of dog rabies in Thailand occurred during 2016-2018. This coincided with the increasing trend in animal rabies cases globally, which started in 2016 and declined in 2017.[2] Longer-lasting outbreaks in Thailand might be due to delays in law enforcement and the local government's ability to mobilize financial resources for immunizing dogs against rabies.[23, 35-37]

The lower incidence of dog rabies in the South region could be attributed to the local population being predominantly Muslim, where their religion discourages dog ownership.[38] In the North and Northeast regions of Thailand, where Buddhists predominate,[24] stray dogs are commonly seen at Buddhist temples.

The number and size of clusters varied by the percentage of the population at risk under scan. Decreasing the percentage would increase the resolution and detect small clusters missed by the high percentage scanning. On the other hand, high resolution will report too many clusters, causing difficulty in visualization due to cluttering of the small clusters. We visually judged that the 15% at spatial risk population setting level struck a balance between the level of cluster detection and the overall comprehensibility of visualizing these clusters. Seven was the optimal number of clusters for visualizing dog rabies incidence rates at the provincial level.

Interestingly, the Northeast region was always the center of significant clusters, regardless of the percentage set for the population at risk. Dogs, both owned and stray, occupy a wide area of the Northeast region of Thailand due to social and environmental factors.[3, 25] However, dog rabies could have spread across borders, and South-East Asia subclades 1, 3, and 4 were found to be present in bordering countries such as Myanmar, Laos, and Cambodia, as well as in Thailand and Vietnam.[39] The size of the clusters affected the number of polygons in each cluster. It is possible that the large cluster size in the Northeast was partly attributed to cross-border transmission within Southeast Asia.

In contrast to previous spatio-temporal cluster studies on rabies in animals in Thailand, which primarily concentrated on the Upper Northeastern region from 2016 to 2018[23] and encompassed various animal cases from 2017 to 2018,[3] our study offers a comprehensive overview of rabies in dogs, covering seventeen years since the launch of a digital database. Another study using sub-districts as a unit of analysis during 2012 - 2017[24] is relevant to our findings from similar periods; our unit of analysis at the province level is worth noting that the Southern and Eastern regions face considerable challenges due to persistent clusters identified before and after the earlier studies. This highlights the need to further explore the factors contributing to the current situation. Moreover, all border provinces remain at risk for clustered occurrences, as they are constantly exposed as a threat to dog rabies cases.

Visualizing spatio-temporal disease clusters on a tilted map gives more compact, better integrated, and more perceivable visual information than the conventional computer-intensive method where multiple maps are required. Our visualization method is among many researchers' attempts to incorporate a time dimension into a 2-dimensional geographic. Several spatio-temporal studies have attempted to represent both space and time dimensions in different ways. One approach was to present the spatial dimension on maps and use color-coded symbols to represent time.[17] However, these methods did not provide a clear perspective on the duration of the cluster. Maps have been used for the spatial dimension, while tables or bar graphs with year on the x-axis have been used for the temporal dimension in various studies.[18, 19, 21, 22] Another study employed multiple maps, each representing a different time period[20] similar to the 2-dimensional dog rabies incidence with geography distribution shown in Figure 3. Our innovative method empowers researchers to better visualize their spatio-temporal data in multiple dimensions, including space, time, and relative risk. By presenting multiple clusters, researchers can conveniently compare each attribute of every cluster, allowing for a more comprehensive data perspective.

Our study used a method to visualize spatio-temporal clusters of dog rabies during a prolonged period. However, a number of limitations should be considered in the interpretation of our study findings. Firstly, our use of the annual human population instead of the dog population might have been an improper presentation of dog rabies incidence as it strayed from the notion of incidence being number of new cases among susceptible populations (of any species). Secondly, the far South region was affected by insurgency violence during the early years of the study period. Difficulty in undertaking government surveillance work during situations of armed conflict could have affected our data quality. Lastly, information technology underwent many changes during the study period, and data quality might have varied over time which could have subsequently affected the validity of our findings.

CONCLUSION

We used a method for the integration of time into a 2-dimensional geography to visualize spatio-temporal clusters of disease outcomes using dog rabies as an example. Based on our results, we recommend intensive control measures such as pulse vaccination with dog population control (3) to alleviate dog rabies, as high-risk clusters were detected throughout Thailand, particularly in the North and Northeast regions.

Declarations

Ethics approval

The study was exempted from ethical approval by the Animal Ethics Committee.

Availability of data and materials

All data generated or analysed during this study are included in this published article [and its supplementary information files].

Competing interests

We confirm that this manuscript has not been published. All authors declare no competing interests. We also have no conflicts of interest to disclose.

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Author contributions

TT, Roles/Writing - original draft; Methodology; Data curation, analysis, and visualization.
KKKH, Methodology; Data analysis and data visualization.
EBM, Data visualization, Writing – review and editing.
WW, Writing - review and editing.
VC: Project administration; Conceptualization; Data visualization; Writing - review and editing.

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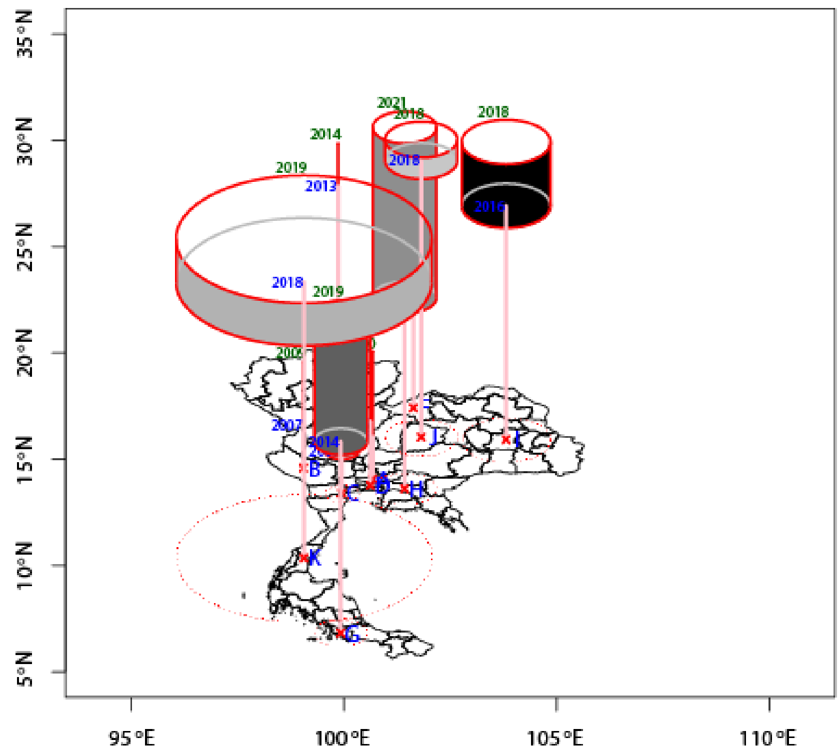
Supplementary

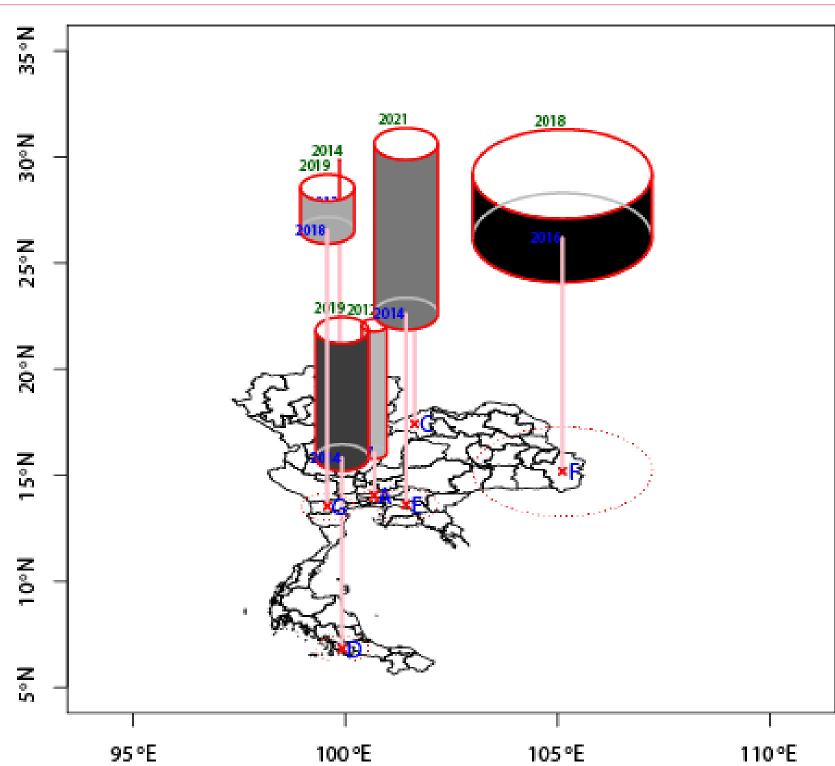
Table showing significant clusters of dog rabies in Thailand from 2005 to 2021 from retrospective space-time scan analysis and Poisson model using a 50% temporal window among 50%, 20%, 15%, and 10% of the population at risk, ordered by start date (p-value <0.01).

Level of the population at risk	START_DATE	END_DATE	LOCATION_ID at Center	LONGITUDE	LATITUDE	RADIUS (×100)	NUMBER OF LOCATION (Region)	LLR	RR	Letter on cylindrical map
50%	2016/1/1	2018/12/31	Buriram	14.81972357	102.9585486	2.397249194	22 (E, C, NE, N)	1415.462691	6.500597812	A
20%	2007/1/1	2010/12/31	Phra Nakhon Si Ayutthaya	14.34408748	100.5280554	0.580285447	6 (C)	109.3922439	2.366709632	A
	2013/1/1	2014/12/31	Chiangrai	19.84498632	99.86692215	0	1 (N)	22.67191371	3.581600413	B
	2014/1/1	2021/12/31	Chachoengsao	13.60606859	101.4305713	0.750827019	6 (E)	617.987635	4.960455908	C
	2016/1/1	2018/12/31	Sisaket	14.85664377	104.3712863	1.92070488	10 (NE)	1330.624611	8.839080215	D
	2018/1/1	2018/12/31	Phetchabun	16.26121466	101.1465339	1.621651305	14 (C, NE, N)	44.96858098	2.47780675	E
15%	2007/1/1	2012/12/31	Pathumthani	14.06405648	100.6832267	0.298079857	2 (C)	137.0663777	2.510434668	A
	2013/1/1	2014/12/31	Chiangrai	19.84498632	99.86692215	0	1 (N)	22.67191371	3.581600413	B
	2014/1/1	2015/12/31	Loei	17.40355827	101.6342269	0	1 (NE)	20.97863983	4.643879829	C
	2014/1/1	2019/12/31	Satun	6.825982799	99.92951733	0.624943633	2 (S)	364.301888	7.165952328	D
	2014/1/1	2021/12/31	Chachoengsao	13.60606859	101.4305713	0.750827019	6 (E)	617.987635	4.960455908	E
	2016/1/1	2018/12/31	Ubonratcha-thani	15.18261244	105.1129187	2.108369054	9 (NE)	1291.41882	9.403559625	F
	2018/1/1	2019/12/31	Ratchaburi	13.53339153	99.58073641	0.633682974	4 (C)	30.02537513	3.183200435	G
10%	2007/1/1	2010/12/31	Pathumthani	14.06405648	100.6832267	0	1 (C)	65.64547931	4.80291904	A
	2007/1/1	2009/12/31	Kanchanaburi	14.58172785	99.05115077	0	1 (C)	15.70771303	3.026723353	B
	2007/1/1	2008/12/31	Samutsong-khram	13.39632643	99.95423422	0.397853559	3 (C)	19.83335682	3.094083976	C
	2008/1/1	2012/12/31	Bangkok	13.77184826	100.6243544	0	1 (C)	97.45164117	2.482499152	D
	2013/1/1	2014/12/31	Chiangrai	19.84498632	99.86692215	0	1 (N)	22.67191371	3.581600413	E
	2014/1/1	2015/12/31	Loei	17.40355827	101.6342269	0	1 (NE)	20.97863983	4.643879829	F
	2014/1/1	2019/12/31	Satun	6.825982799	99.92951733	0.624943633	2 (S)	364.301888	7.165952328	G
	2014/1/1	2021/12/31	Chachoengsao	13.60606859	101.4305713	0.750827019	6 (E)	617.987635	4.960455908	H
	2016/1/1	2018/12/31	Roi Et	15.91784475	103.8161167	1.043326856	7 (NE)	1202.146578	11.44342042	I
	2018/1/1	2018/12/31	Chaiyaphum	16.02972145	101.8195719	0.84907219	3 (NE, N)	14.13254458	2.468806692	J
	2018/1/1	2019/12/31	Chumphon	10.34487042	99.06248371	3.006913731	11 (S, C)	107.7186076	3.413922187	K

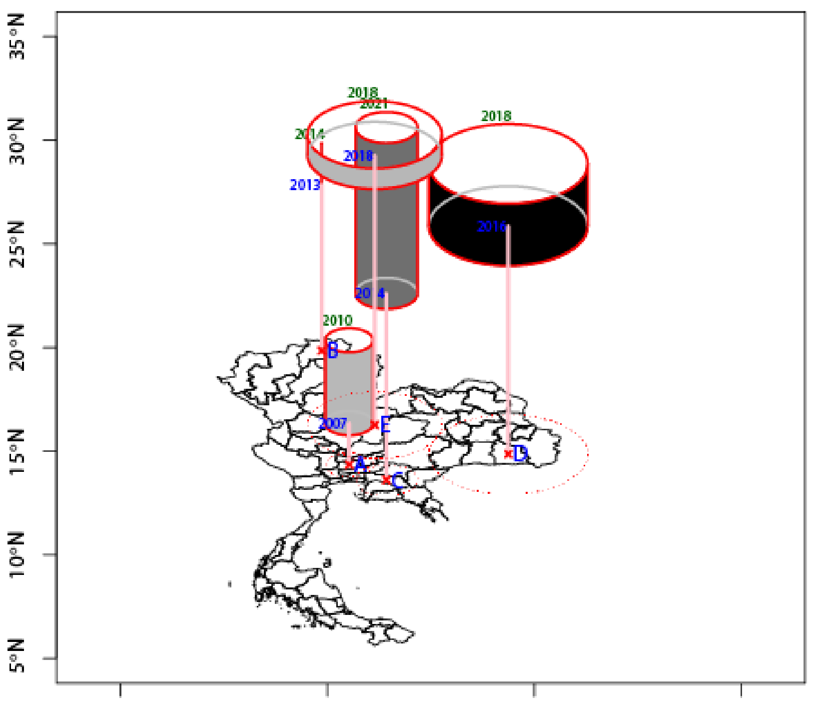
C, Central; N, North; NE, Northeast; E, East; S, South; RR, Relative risk; LLR, Likelihood ratio



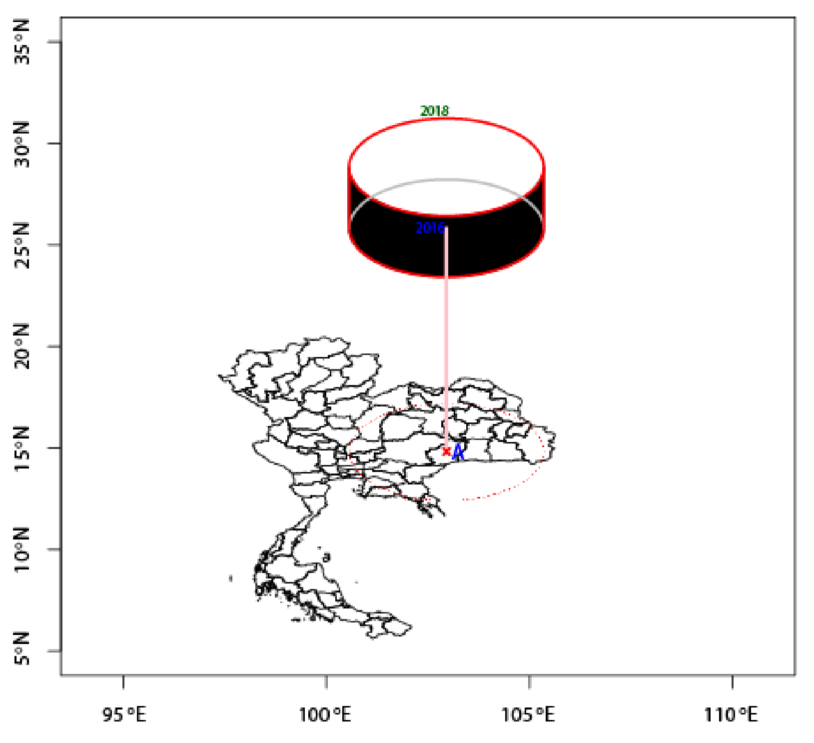
Supplementary Material Figure 1. Spatio-temporal clusters of dog rabies in Thailand during 2005-2021, using a 50% temporal window and 10% of the population at risk



Supplementary Material Figure 2. Spatio-temporal clusters of dog rabies in Thailand during 2005-2021, using a 50% temporal window and 15% of the population at risk



Supplementary Material Figure 3. Spatio-temporal clusters of dog rabies in Thailand during 2005-2021, using a 50% temporal window and 20% of the population at risk



Supplementary Material Figure 4. Spatio-temporal clusters of dog rabies in Thailand during 2005-2021, using a 50% temporal window and 50% of the population at risk