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Association of socioeconomic factors and transport network with dengue incidence in Bangkok -Thailand

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Association of socioeconomic factors and transport network with dengue incidence in Bangkok -Thailand

Abstract

Objective: The objectives of this study are to address the impact of several socioeconomic factors and the transport network on dengue incidence within Bangkok over a two-year period: 2012 and 2013. It also focuses on developing public transport data to identify the spatial distribution of dengue virus at the khwaeng level.

Methods: Three socio-economic variables previously identified as having associated dengue risk were studied: percentage area covered by cement houses, proportion of population aged 6 years and above who never studied and number of houses. Cross correlation analyses of dengue incidence in 2012 and 2013 between selected dispersed khwaeng were conducted to assess spatio-temporal correlations. Then, the impact of inter-khwaeng transport connectivity was included in the spatio-temporal cluster analyses along with the socio-economic variables to identify any dengue hotspots during the 2 years period. Finally, a detailed origin destination matrix for public transport network was constructed to enable more in-depth analyses of the role of intra-urban transport on dengue hotspots.

Results: The cross correlation showed evidence of significant lagged correlations in dengue incidence rate between khwaeng, suggesting that connectivity may play a role in the spatial distribution of dengue. Several spatio-temporal dengue clusters with varying size and duration and relative risk were detected. Whilst the three socio-economic variables did explain a significant amount of the relative risk, transport connectivity was also important, especially during the dry season.

Conclusion: There was clear significant impact of several socioeconomic risk factors associated with dengue in the spatial analyses in Bangkok. Khwaeng connectivity also played a role in the creation of dengue hotspots in the dry season. A more detailed analysis using the actual mobility patterns at varying times of year and the origin destination matrix generated would improve this approach.

Key words: Dengue, socioeconomic, transport network, incidence, khwaengs

Association des facteurs socio-économiques et du réseau de transport avec l'incidence de la dengue à Bangkok -Thaïlande

Résumé

Objectif : Les objectifs de cette étude sont d'aborder l'impact de plusieurs facteurs socio-économiques et du réseau de transport sur l'incidence de la dengue à Bangkok sur une période de deux ans : 2012 et 2013. Elle se concentre également sur le développement de données sur les transports publics pour identifier la distribution spatiale des virus de la dengue au niveau des khwaengs.

Méthodes : Trois variables socio-économiques précédemment identifiées comme présentant un facteur de risque pour la dengue ont été étudiées : pourcentage de superficie couverte par les maisons en ciment, proportion de la population âgée de 6 ans et plus n'ayant jamais étudié et nombre de maisons. Des analyses de corrélation croisée de l'incidence de la dengue en 2012 et 2013 entre plusieurs khwaengs ont été menées pour évaluer les corrélations spatio-temporelles. Ensuite, l'impact de la connectivité des transports a été inclus dans les analyses de cluster spatio-temporelles avec les variables socio-économiques pour identifier les groupements de forte incidence de dengue au cours de la période de 2 ans. Enfin, une matrice origine-destination détaillée pour le réseau de transport public a été construite pour permettre des analyses plus approfondies du rôle du transport intra-urbain sur les groupements où l'incidence de la dengue était élevée.

Résultats : La corrélation croisée a montré des preuves de corrélations retardées significatives dans le taux d'incidence de la dengue entre khwaengs, suggérant que la connectivité peut jouer un rôle dans la distribution spatiale de la dengue. Plusieurs groupements spatio-temporelles de dengue de taille, de durée et de risque relatif variables ont été détectées. Alors que les trois variables socio-économiques expliquaient une part significative du risque relatif, la connectivité des transports a également joué un rôle important, en particulier pendant la saison sèche.

Conclusion : Il y a un impact clair de plusieurs facteurs de risque socio-économiques associés à la dengue dans les analyses spatiales à Bangkok. La connectivité des khwaengs a également contribué à la création de points chauds de dengue pendant la saison sèche. Une analyse plus détaillée utilisant les modèles de mobilité réels à différentes périodes de l'année et la matrice origine destination générée améliorerait cette approche.

Mots clés : Dengue, socio-économique, réseau de transport, incidence, khwaengs

List of abbreviations

BMA	Bangkok Metropolitan Administration
CCM	Cross Correlation Function
CDR	Call Detail Records
DENV	Dengue Virus
GPW	Gridded Population of the World
GTFS	General Transit Feed Specification
MRT	Metropolitan Rapid Transit
NSO	National Statistical Office of Thailand
OD	Origin - Destination
OSM	OpenStreetMap
POI	Point of Interest
QGIS	Quantum Geographic Information System
RR	Relative Risk
UTM 47N	Universal Transverse Mercator 47N
WGS 84	World Geodetic System 84

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1. Introduction

1.1. Dengue disease

Dengue is a mosquito-borne viral infection of the Flaviviridae family, dengue virus (DENV), transmitted via the bite of the female mosquito *Aedes aegypti* and other secondary vectors such as *Aedes albopictus* (1). It is the most important infectious disease transmitted to humans by arthropods (2). Four antigenically distinct serotypes of the virus are responsible for dengue: DENV-1, DENV-2, DENV-3 and DENV-4 (3). Infection with one serotype does not induce immunity against other serotypes, therefore a person can become infected more than once. Although the majority of DENV infections are subclinical, resulting in insufficient discomfort for clinical consultation (4), any of the 4 serotypes can cause dengue fever, an acute viral infection characterized by fever, joint and muscle pain, rash, severe headache and nausea, as well as more severe forms of the disease: dengue haemorrhagic fever that lead to bleeding from the nose and the gums and dengue shock syndrome (1). After the bite of an infected female mosquitoes, the incubation period in human ranges from 3-12 days and the duration of infection lasts for a similar period of time (1). Infected individuals can infect mosquitoes that bite on them irrespective of whether there is visible disease and throughout the period of infection (5).

In the recent years, increased population growth specially in tropical cities with poor waste and water management and uncontrolled and unplanned urbanization has led to the surge of DENV. Moreover, rising temperatures, global climate change, humidity and rainfall that determine mosquito and especially *Ae. aegypti* distribution, abundance and capacity to transmit the virus, all influence the epidemiology of dengue (6).

This is why, in 2019, DENV was considered by the World Health Organization one of the top 10 global health threats (7). 96 million of symptomatic cases are estimated to occur internationally each year while 390 million dengue virus infections occur per year (1). Over the past decade, the number of dengue outbreaks has escalated and the population at risk is increasing yearly in many countries mainly in Asian and Latin American countries with tropical and subtropical climates. Human migration and international trade and travel are constantly introducing new vectors and pathogens into novel geographic areas and thus contributing to the global distribution of dengue (4). More than 3.5 billion people are at risk of DENV infection (8).

Dengue epidemics tend to occur during and after the rainy season when there is a high number of mosquitoes and favorable temperatures. *Ae. aegypti* is highly adapted to the urban environment, is active

during the day and has a small flight range (3). Although once considered a pediatric disease, there is today an increasing number of cases in individuals over 15 years (9).

1.2. Dengue in Bangkok- Thailand

The first dengue outbreak in Thailand was observed in 1958 as Dengue Hemorrhagic Fever (DHF). By the late 1970s, the disease was widespread among countries in Southeast Asia and DHF had become a leading cause of hospitalization and death among children in Thailand. It has had since then a huge burden of dengue for more than half a century due to high population density, rapid urbanization, inadequate infrastructure and climatic conditions (10). Nowadays, a nationwide surveillance system exists where inpatient and outpatient dengue cases are reported from all government medical institutions and some private hospitals and clinics (10). The Thai Ministry of Public Health (MoPH) and Bangkok Metropolitan Administration (BMA) report dengue confirmed cases from the hospitals via an online operating system "Epi-net" (11). According to this notification, the mosquito control intervention is activated, which is mainly based on fumigating pesticides within 100 m² areas of the patient's home and surrounding area. Some of the major challenges facing this strategy have been the delays associated with clinical confirmation and reporting of cases, followed by the difficulty to track the addresses of identified cases (11). Most dengue fever cases occur in people between 5 and 24 years old, although the age group with the highest incidence in Thailand has shifted from 5-9 years old to 10-14 years old. The incidence rate per 100,000 people aged 5-9 years dropped from more than 800 in 2001 to less than 700 in 2002, while the incidence rate for people aged 10-14 remained above 700 per 100,000 people during the same period. In the following years, the incidence of both age groups declined (12).

Bangkok is the capital of Thailand with a population of 10.5 million as of 2020. According to the 2010 census, Bangkok had a population of 8.3 million, out of which 4.3 million were registered (13). It has an area of 1569 km² and is crossed by the Chao Phraya River. It is now divided into 50 administrative districts called Khets and 180 sub-districts called Khwaengs. In the Southeast Asia region, Bangkok has one of the largest populations after Jakarta and Manila. The population density is concentrated in the center, with areas along major transportation links being more densely populated (14). The center of Bangkok has dense concentrations of commercial activity, notably around Khao San Road, Sukhumvit, Siam Paragon, Silom, and Yaowarat (15).

The seasonal peak of dengue fever cases and deaths occurs between May and October each year, which coincides with the rainy season in Bangkok. During this season, rainfall increases, resulting in an increase in the density of mosquito populations and an increase in their vectorial capacity (16). This is mainly due

to the increase in mosquito bites and accelerated virus development (10). In Bangkok, temperature fluctuates year-round ranging from 22-35 °C on average, but can soar to 40 °C in March-May. In addition to the effects of meteorological factors on dengue incidence, several studies identified socio-economic risk factors for dengue. A study done in São Paulo found that the relative risk of dengue increased significantly in the age group older than 14 years as the level of socio-environmental deprivation increases, suggested that dengue was associated with low socioeconomic status (17).

1.3. Dengue and public transportation

The study of public transportation mobility patterns can be used to monitor disease spread (18). Though it may be complex, studies have taken varied approaches to analyze its impact on the spread of dengue. A study done in Kaohsiung, Taiwan found that approximately 75% of dengue fever cases were located within 1.0 km of a major road, although spatial patterns differed by year (19). Another study in Guangzhou, China developed risk indices from transport network and ridership data, and showed that the yearly incidence rate of dengue was much higher in neighborhoods that were close to metro stations with high traffic volume (20). Lately, new ways to measure human mobility using mobile phone and social media within and between cities have been studied to assess their impact on the spatial diffusion of infectious diseases.

Within Bangkok, the advanced public transportation systems facilitate the movement of people and accelerate the distribution of the virus around the city, since the flight range of *Aedes aegypti* is limited. In fact, the population inflates up to 15 million during the day mainly due to commuters from surrounding areas (21). Dengue-infected travelers can transmit the disease in both their home and work environments, leading to larger scale diffusion of the virus (22). When susceptible vectors are present in these new areas, there is the potential for local transmission to be established. The dispersion of dengue is also affected by where people go to within a city and urban activity such as crowd gathering in city centers.

The public transport in Bangkok consists of the Bangkok Mass Transit System (BTS): skytrain, the underground metro: Metropolitan Rapid Transit (MRT) and Chao Phraya Express and shuttle boats. It also has a large bus network, tuk-tuks and taxis.

Therefore, understanding the spatial and socioeconomic distribution of risk associated with dengue disease at a sub district level could help assign probable risk to an area and therefore enable early vector control targeted interventions and prevent frequent outbreaks.

2. Objectives

This study aims at addressing the impact of several socioeconomic factors and the transport network on dengue incidence within Bangkok over a two-year period: 2012 and 2013. It also focuses on developing public transport data to identify the spatial distribution of DENV at the sub districts level.

3. Methods

3.1. Data sources

3.1.1. Dengue Incidence Data

The data consisting of dengue cases was obtained from the Health Department of the Bangkok Metropolitan Administration (BMA) for 2012-2013. These data comprise individual case data aggregated to the district (khet) and sub district (khwaeng) level on a weekly and monthly basis. In 2012, 10 081 dengue cases were reported, while in 2013 this number increased to 15 046.

3.1.2. Socioeconomic variables

The dataset with socioeconomic variables was obtained from the 2010 census data conducted by the National Statistical Office of Thailand (NSO). It included sub-district level aggregated data on education, nationality, religion, work status, work type, geographic area, number of households, population, age group, type of houses and housing, type of water sources, different household amenities (eg: refrigerator, air conditioner, washing machine...) and other means of transportation and communication.

For this study, we looked mainly at the percentage area covered by cement houses, the proportion of population aged 6 years and above who never studied and the number of houses. These three socioeconomic variables were chosen because they were found to be strongly associated with dengue risk in a previous analysis of these data done by Rojina Karki, an alumni of the MPH at EHESP, who explored the meteorological and socio-economic factors associated with increased risk of dengue at the sub-district level (23). In fact, in regard to the type of construction, there are lower temperatures and higher humidity inside cement and brick houses, which are favorable for adult mosquito survival (24). Moreover, household income and thus indirectly household condition, cleanliness and number of mosquitoes are generally correlated with the level of education. Finally, population density is also a known risk factor for dengue transmission, both at a household or at an area level (25).

3.1.3. Access to transport

The public transport network data as well as the road network were taken from the Bangkok Metropolitan Authority (BMA), OpenStreetMap (OSM), and TransitBangkok. The 3767 bus, metro and ferry stops and the 209 lines that make up Bangkok's public transport network were aggregated and visualized using QGIS 3.10.13. The number of stations per square kilometer for each Khwaeng was calculated by dividing the number of stations by the total area in square kilometers of each Khwaeng.

3.2. Analysis

Graphs were used to understand the distribution of dengue disease and its trend and to visualize the cross correlations of dengue incidence rates among Khwaeng. Maps were used to display population density and average distance between sub districts.

This graph (Figure 1) summarizes dengue cases per month over the 2 years' period.

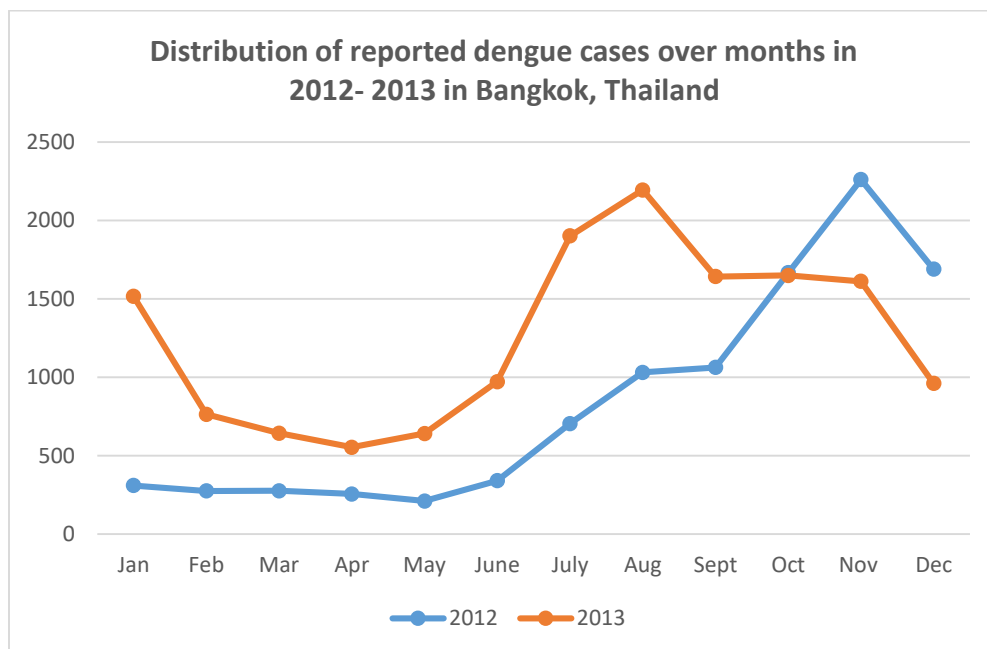


Figure 1: Monthly distribution of reported dengue cases in 2012 and 2013 in Bangkok, Thailand

3.2.1. Cross Correlations

In a first step, cross correlations were calculated to see if there was any evidence of dengue of significant correlation at different lag times to indicate a possible role of human mobility between specific Khwaengs. Cross correlation functions were calculated using Genstat version 20. Since it was challenging to do all the

correlations among 160 Khwaengs; we randomly selected 18 central and peripheral (North, South, East, West). The max lag month was set to 4 months. This seemed more biologically sensible and reduced the number of degrees of freedom.

3.2.2. Satscan analysis

To explore how dengue case spatial hotspots were influenced by the three socioeconomic variables and the transport connectedness, SaTScan v9.7, a software that analyses spatial, temporal and space-time data was used (26).

SaTScan enabled us to detect and evaluate the statistical significance of high dengue clusters. It uses a poisson-based model, where the number of events in a geographical area is Poisson-distributed, according to a known underlying population at risk. SaTScan adjusts to inhomogeneity of a background population and to the covariates that were added.

The standard purely spatial scan statistic imposes a circular window on the map. The window is in turn centered on each of several possible grid points positioned throughout the study region. For each grid point, the radius of the window varies continuously in size from zero to some upper limit specified by the user. In this way, the circular window is flexible both in location and size. In total, the method creates an infinite number of distinct geographical circles with different sets of neighbouring data locations within them. Each circle is a possible candidate cluster. The space-time scan statistic is defined by a cylindrical window with a circular geographic base and with height corresponding to time. The base is defined exactly as for the purely spatial scan statistic, while the height reflects the time period of potential clusters. The cylindrical window is then moved in space and time, so that for each possible geographical location and size, it also visits each possible time period. In effect, we obtain an infinite number of overlapping cylinders of different size and shape, jointly covering the entire study region, where each cylinder reflects a possible cluster.

For the Poisson model, the expected number of cases in each area under the null-hypothesis is calculated using indirect standardization. Without covariate adjustment the expected number of cases in a location is:

$E[c] = p * C / P$ where c is the observed number of cases and p the population in the location of interest, while C and P are the total number of cases and population respectively.

To include covariates, c_i , p_i , C_i and P_i are defined in the same way, but for covariate category i . The indirectly standardized covariate adjusted expected number of cases for spatial analysis is:

$$E[c] = \sum_i E[ci] = \sum_i p_i * C_i / P_i$$

For our analysis, we used the residual of the dengue cases per sub-district per month after the significantly associated meteorological variables had been regressed out. The resulting residual values were then rounded up or down to the nearest integer. Four spatio-temporal hotspot cluster analyses were then performed over the entire 2-year period. Residual dengue data only, the dengue data with the number of connections per sub-district, the dengue data with the three socio-economic co-variables (percentage area covered by cement houses, percentage of education, number of houses) and the dengue data with both the number of connections per sub-district and with the three socio-economic co-variables. Because SatScan can only incorporate categorical covariates, the socio-economic and transport variables were categorized by fitting a normal distribution to yield 10 different groups with approximately the same number of khwaeng per group.

For the spatio-temporal analysis, we used the Discrete Poisson model, where the expected number of cases in each area is proportional to its population size. The maximum temporal window for a hotspot cluster was set to 3 months in part to reflect the maximum lag time identified in the cross correlation function analysis and also to avoid having too many or too few clusters. The maximum spatial window was set to 5% given the highly spatially clustered nature of dengue outbreaks. Only clusters with no geographical overlap were allowed. We then performed the same analyses for the dry season (December-May) to examine any seasonal effects. This was repeated for just the very dry season (February-May) to exclude any spill-over effects from the wet season. A significant P value threshold was set to $P < 0.004$ to account for the twelve analyses (Bonferroni correction). This criterion only led to the exclusion of eight clusters across all analyses; the other clusters all being significant at P values below 10^{-3} .

3.2.3. Spatial description of transport network

To further assess the population density and the transport network in Bangkok, we built a population grid and an Origin Destination matrix.

Building a population grid

A population grid was designed for the BMA territory using two databases: The first one, “The Gridded Population of the World (GPW v4)”, models the distribution of human population (counts and densities) using census data. Population estimates are created by extrapolating the raw census counts to estimates for target years 2000, 2005, 2010, 2015, and 2020. The two basic inputs of GPW are non-spatial population data and spatially-explicit administrative boundary data. These data are collected from hundreds of

national agencies and statistics offices and some other organizations such as the United Nations (27). The second one, “The Oak Ridge National Laboratory (ORNL) LandScan”, is a community standard for global population distribution data, representing an ambient population distribution averaged over 24 hours. The modeling process uses spatial data and socioeconomic and cultural understanding of an area. The population distribution model calculates a “likelihood” coefficient for each cell and applies the coefficients to the census count (28). A manual correction was then made. Both databases present their results in continuous global raster surfaces at approximately 1 km (30” X 30”) spatial resolution.

Using QGIS 3.16 and its SAGA extension, we first clip raster layers according to BMA territory shapefile. 2063 cells (30” X 30”, approximately 1 km) were selected for each LandScan layers of 2012 and 2017 and GPW layers of 2010 and 2015. Using SAGA’s “raster values to points” tool, a new point-based vector layer was created. This tool allowed the aggregation of the population counts of each raster layers into a single vector point-based layer based on the centroids of the cells.

Using the same tool in SAGA, a polygon-based grid was created as well. Both layers were projected in WGS84 UTM 47N.

Using QGIS tool “Join attributes by location” and based on the centroids location, administrative information about the Khwaengs /Khets geocodes and names from the 160 Khwaengs SHP layer were added to these two new layers. For the 159 centroids located outside the BMA territory, we returned to their cell location to add the appropriate administrative information.

To assess the variation of the population count from one database to another, we retrieved the population counts from the cells of each database and after aggregating them, we compared them with the NSO data for 2010.

Origin destination matrix for public transport network

After excluding 8 cell centroids that were outside the BMA territory (N=2055) we used QGIS Network Analysis Tools (QNEAT3) to create an Origin-Destination Matrix between the 2055 cells using the public transport network Shapefiles (in-bound and out-bound lines, N=393). Since we were looking at calculating more than 4.2 M. trips and ultimately aggregating the results at Khwaeng level, we opted for an OD matrix stored directly in CSV and without generating any geometry. For similar reasons, we did not use the 4819 bus/ferry/metro stations as entry/exit points to the network. As the average distance calculated with QGIS 3.16 between the stations is 96 meters, we do not expect this to be a major source of bias for the interpretation of the OD matrix results. The OD-Matrix from Points as CSV (n:n) algorithm computes the

network route-based cost of Origin-Destination relations between the points inside a single layer (n:n, here the 2055 cells' barycentres). The algorithm is searching for the shortest path between two points. Costs components are split up into Entry-Cost (Euclidian distance between the point of origin to the network), Network-Cost, Exit-Cost (Euclidian distance between the network and the point of destination) and Total Cost (sum of all cost components). The data are then stored as rows in a CSV File. A topology tolerance of 400 meters was set up to account for the possibility for travelers to transfer from one lane to another by foot. This 400 m distance (or 5 minutes walking-distance) is a standard threshold in the literature on public transports, although such distance has been the source of many debates (29).

4. Results

4.1. Asynchrony of dengue cases among Bangkok sub districts

The cross correlation showed evidence of significant asynchrony and not the same lag in the pairs of khwaengs that were selected nor same level of significance. The table 1 summarizes the results of the CCF between 10 selected khwaengs (Cf. annex 1 for complete table with the 18 khwaengs). Since we used 4-month as a maximum lag, the chi-2 values (S) significance levels were 0.05*: 9.488, 0.01**: 13.277; 0.001***: 18.467. The results were displayed as follow: Stat S/lag month/CCF.

Table 1: Results of the CCF between 10 selected khwaengs

Khwaeng	100107	100701	100101	102501	101204	101602	103501	103004	103302	101106
100107		31.29/-4/0.658	10.08/-3/5.61	21.61/-1/0.59	18.4/-3/0.48	25.5/-1/0.64	17.5/-3/17.2	1.15/+1/-0.26	2.58/0/0.357	27.4/-3/0.722
100701			5.28/+1/0.784	14.1/0/0.858	10.96/0/0.826	5.53/0/7.35	5.49/0/0.816	5.26/-1/0.324	3.89/0/0.584	22.6/-2/0.658
100101				13.5/-1/0.672	9.37/0/0.728	5.26/0/0.431	9.76/0/0.685	1.99/-2/0.203	9.03/-1/0.572	11.64/0/0.474
102501					7.88/0/0.747	6.1/0/0.7	2.08/+1/0.754	6.3/-1/0.357	3.41/0/0.666	15.65/+1/0.577
101204						5.3/+1/0.669	7.19/0/0.763	10.93/-1/0.466	5.06/0/0.693	16.4/0/0.562
101602							11.81/0/0.748	5.18/-1/0.341	4.5/0/0.448	20.73/0/0.671
103501								7.42/-3/0.3598	7.23/0/0.567	20.03/-2/0.589
103004									3.94/0/0.457	4.05/+1/0.2
103302										5.54/-3/0.367
101106										

As an example, there was significance of lag correlation between khwaeng 100107 and 101106 (south east) with very strong 3-month negative lag.

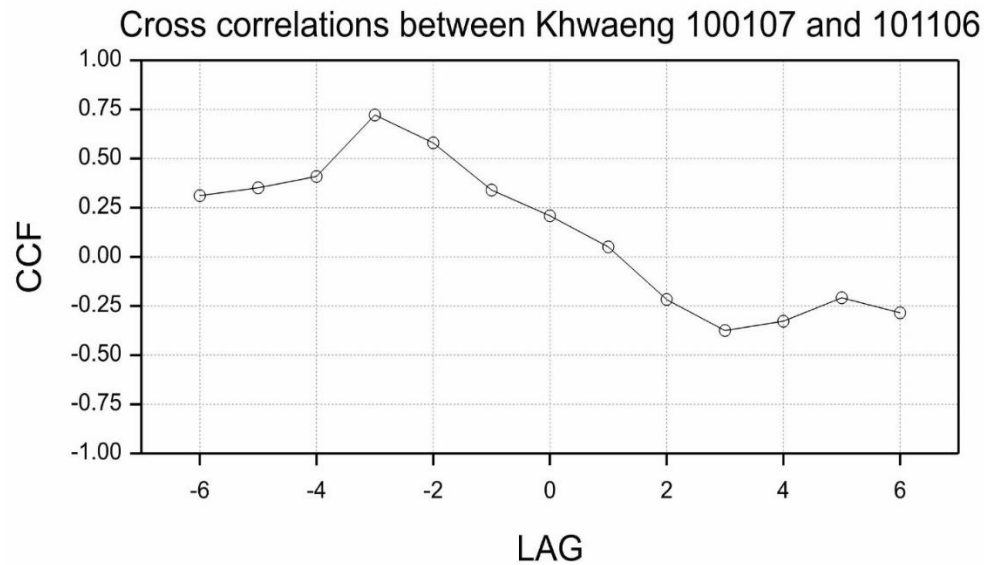


Figure 2: Cross correlation function between a central Khwaeng 100107 and a south eastern one 101106

4.2. Clusters using SaTScan

In the analysis with no covariates, 5 clusters were detected of which one included only one Khwaeng (Figure 3). The 4 large clusters (covering from 10 to 38 khwaeng) occurred during months 8-13 all with a duration of 3 months. The cluster including 38 khwaeng was the second smallest in size (radius 3.2 km) and yielded a very large relative risk (RR) (27.6). Over all the clusters, the size ranged from 2.5-12.6 km and the RR from 3.1-27.6. The means of duration, sub-district number, RR and size are given in figure 4.

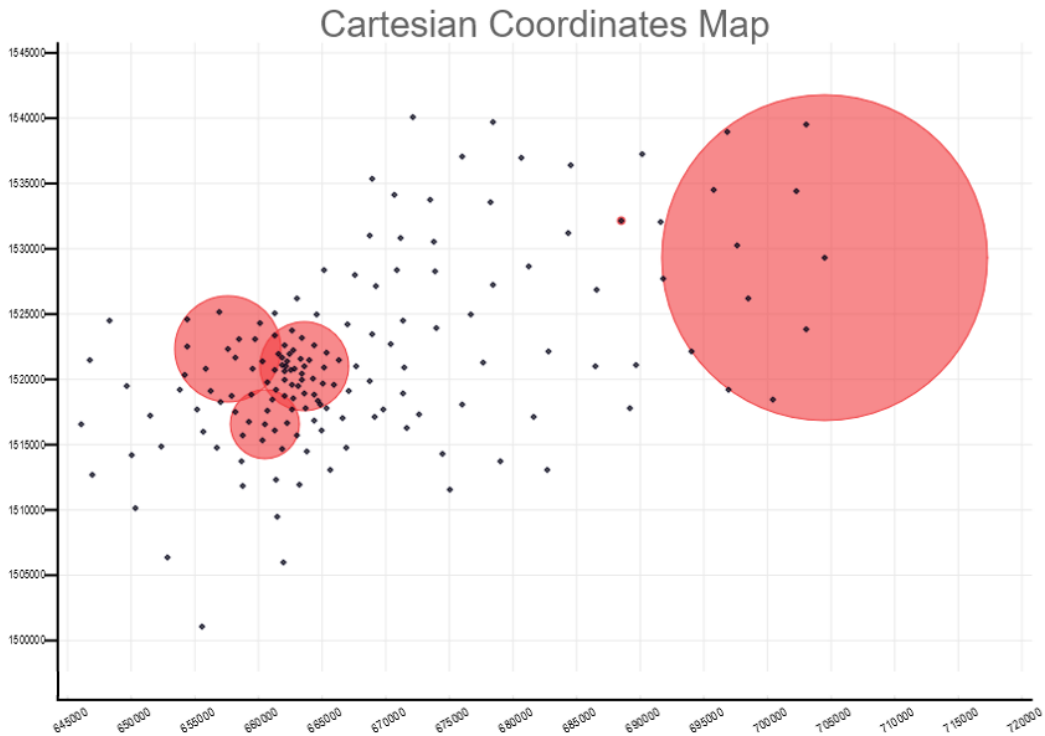


Figure 3: Dengue case hotspots detected through SaTScan analyses with no covariates

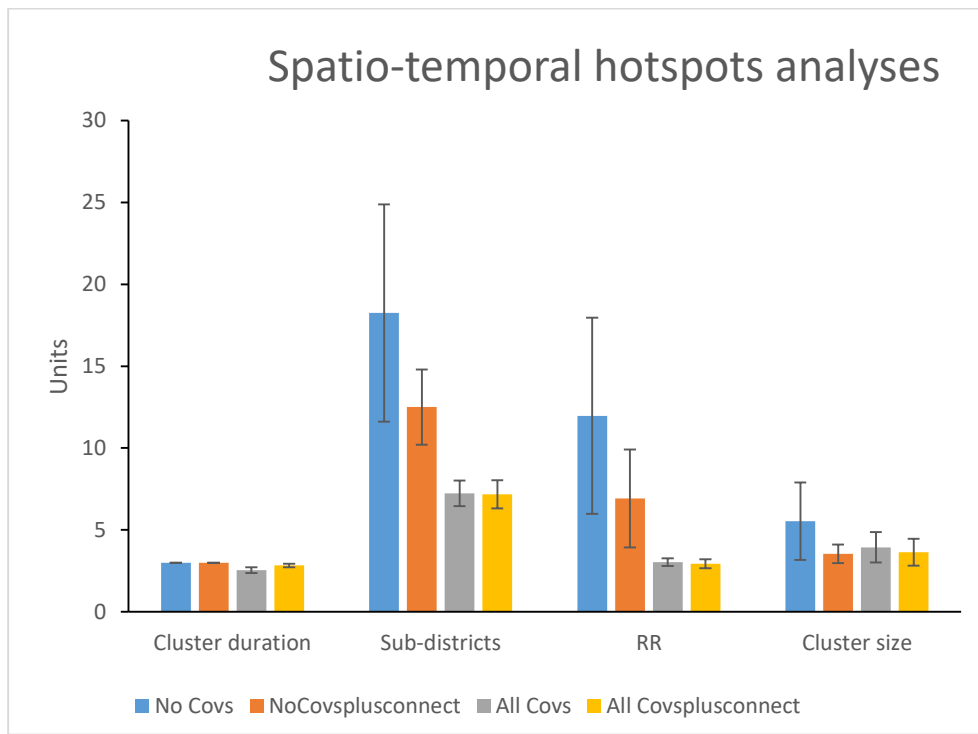


Figure 4: Summary of the spatio- temporal hotspots analyses

Inclusion of number of transport connections as a covariate altered the cluster size, place and disposition. Eight clusters were identified, six of which included more than one sub-district (Figure 5). The timing of the clusters was different from that of the previous analyses, with clusters occurring in months 10-13 and 19-22. Cluster size, number of khwaeng and RR all decreased (ranges 1.8-5.3 km, 7-22 khwaeng and RR 2.2-20.5) and the means and dispersion can be seen in figure 4.

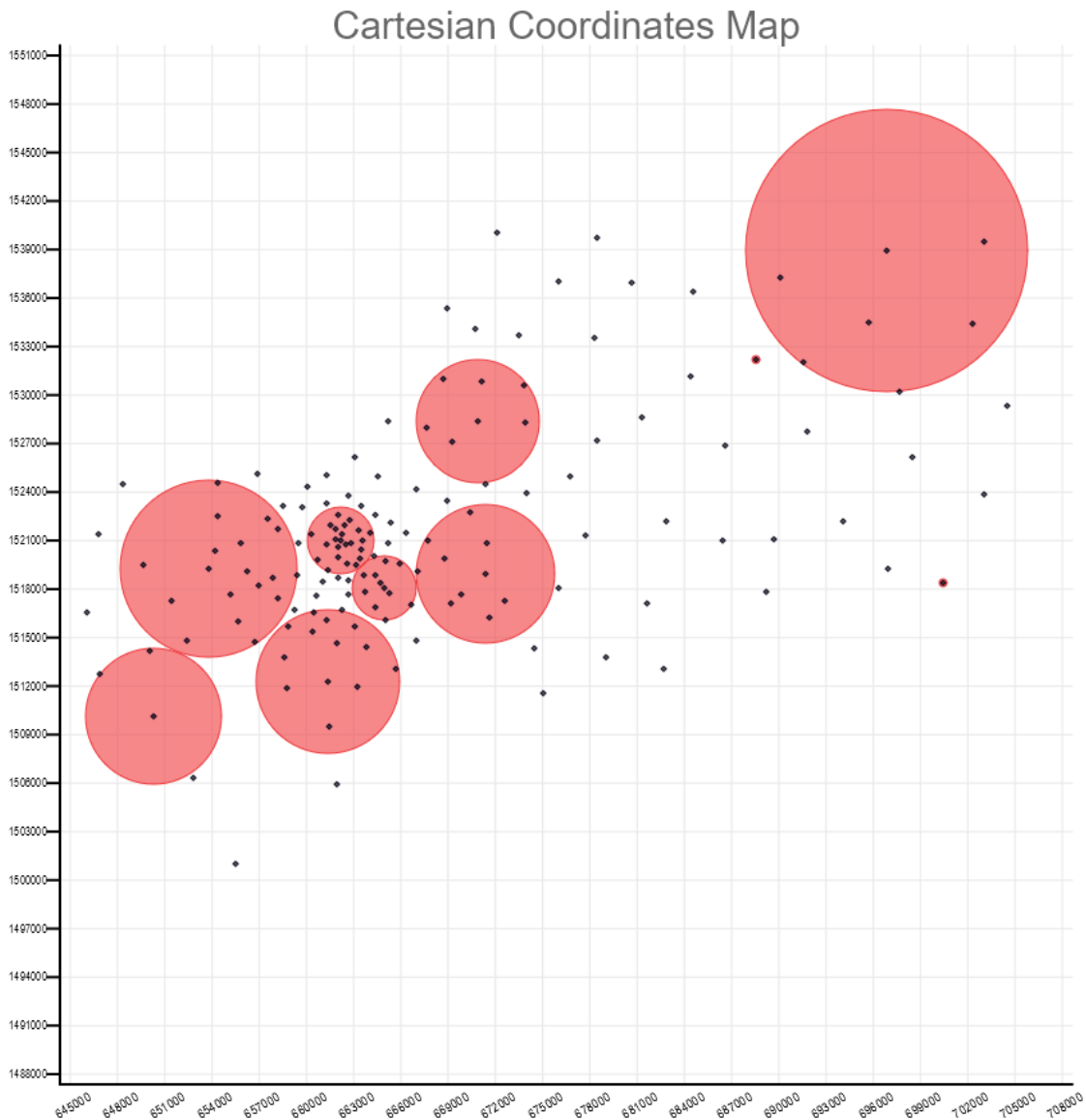


Figure 5: Dengue case hotspots detected through SaTScan analyses with number of transport connections per sub-district as a covariate.

Analysis including the three socio-economic variables but without transport connections generated 15 clusters of which two covered only single khwaeng (Figure 6). The timing of the clusters was spread over the months 9-13 and 19-22. Cluster size, number of khwaeng and RR all decreased as compared to the

analysis with no covariates (ranges 1.1-9.4 km, 3-11 khwaeng and RR 2.2-4.9) and the means and dispersion can be seen in Figure 4.

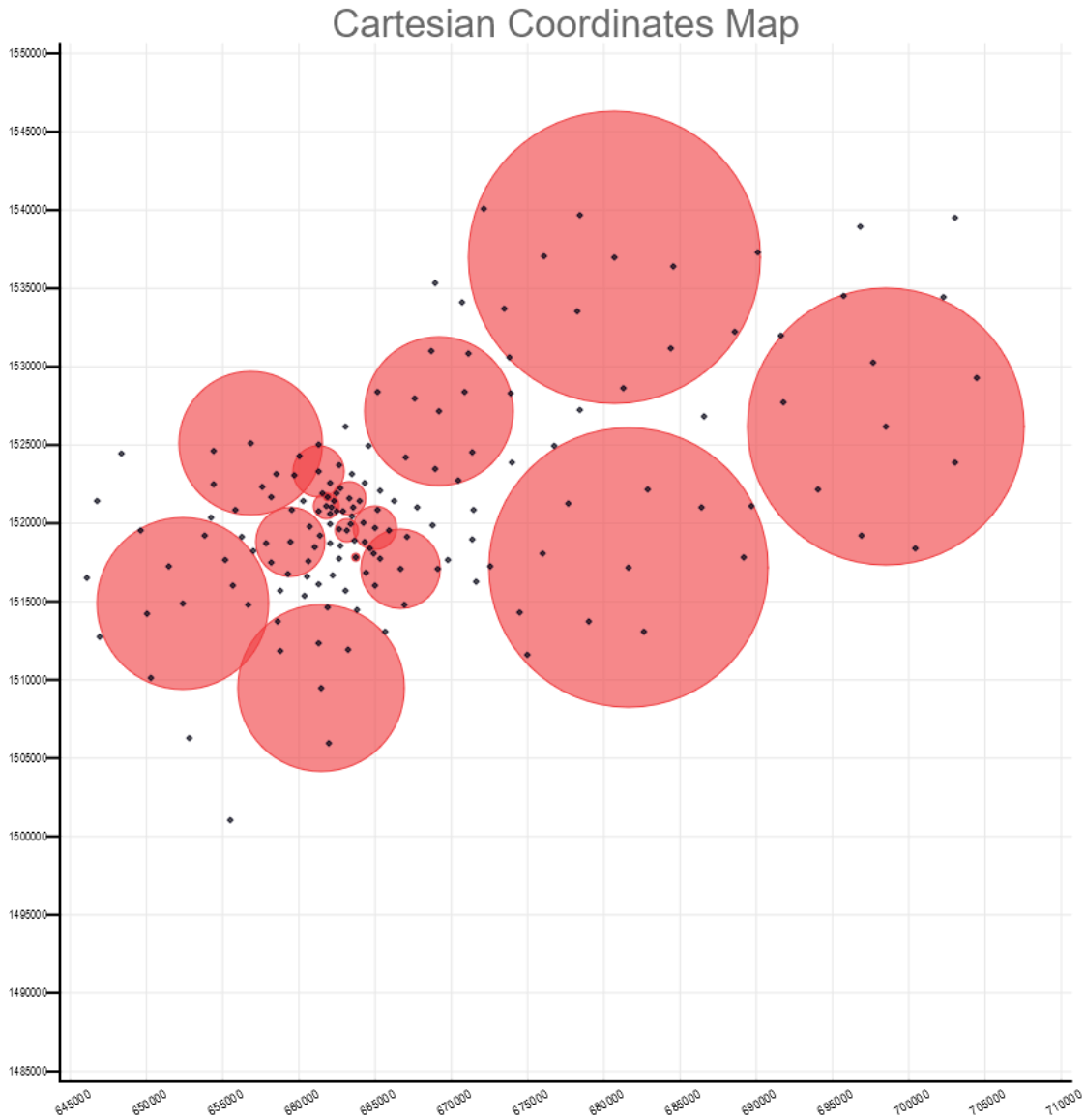


Figure 6: Dengue case hotspots detected through SaTScan analyses with number of houses, %cement houses and %education level per sub-district as covariates

Finally, the analysis including all four covariates yielded 14 significant clusters of which two covered single khwaeng (Figure 7). The timing of the clusters was again spread over months 10-13 and 19-22. Cluster size, number of khwaeng and RR all decreased as compared to the analysis with no covariates (ranges 1.1-8.8 km, 3-12 khwaeng and RR 2.1-4.9) and the means and dispersion can be seen in Figure 4.

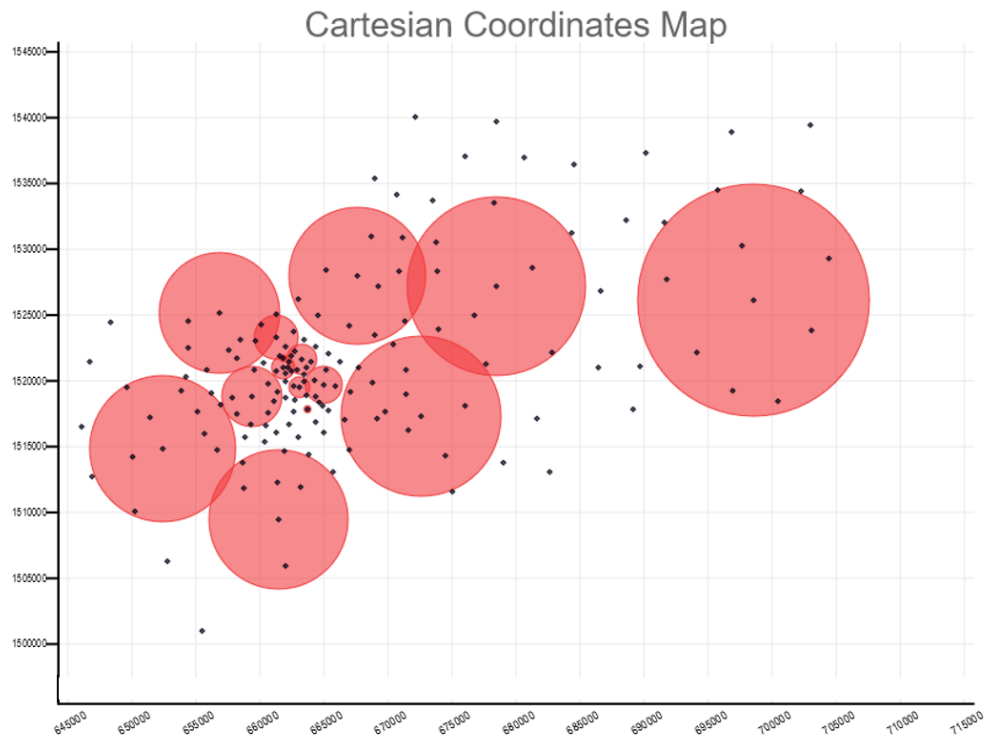


Figure 7: Dengue case hotspots detected through SaTScan analyses with number of transport connections, number of houses, %cement houses and %education level per sub-district as covariates.

As expected, inclusion of the spatially varying covariates altered significantly the disposition of the identified dengue hotspots. There was a dramatic decrease in the mean RR associated with the hotspots from 12 to 3 upon inclusion of the socio-economic variates. Whilst there was also a large decrease upon inclusion of transport number, it was less important and notably changed very little upon inclusion along with the three socio-economic variables. This largely reflects the initial findings in the regression analysis performed by Lefebvre, B. Karki, R. et al. (23) where transport number was the least significant of the four variables ($P=0.013$). Nevertheless, it is interesting to note how the importance of dengue-associated variables can be visualised through this spatial analysis and how their inclusion alters the geographical distribution of the hotspots.

Of the three socio-economic variables, the number of houses had the largest impact, with its inclusion, as compared to the analysis without covariates, decreasing the mean RR to 3.6 averaged over the 13 identified clusters. The percent of cement houses and the level of education only reduced the mean RR to 6.6 and 6.4 respectively averaged over 6 clusters identified in either analysis. This again reflects the

regression analysis where the number of houses was the strongest socio-economic variable associated with increasing risk of dengue.

Insofar as the majority of dengue cases occur during the monsoon period (June to November) and that socio-environmental factors may impact differentially during the wet and dry seasons (particularly with respect to mosquito oviposition sites and thus densities), a hotspot analysis including only the dry season months was then performed. Surprisingly, although there were modifications in the cluster number, size and associated relative risk, the differences were marginal as compared to the previous analysis. Moreover, the relative effects of including the socio-environmental and transport factors were very similar to the previous analysis. Inclusion of the socio-environmental factors significantly decreased the number of khwaengs per cluster, the relative risk and the cluster size (Figure 8). As before the additional effect of including transport with these other covariates made no difference. One notable feature was that the hotspots all occurred immediately after the November period (months December to March), suggesting that the observed hotspots may be carry over from the preceding monsoon season. Thus, we excluded the two months following the monsoon period to attempt to reduce any carry over effects. Once again, whilst there were differences in cluster number, size and relative risk, the overall pattern of the impact of inclusion of the covariates was very similar to previously, with the socio-environmental variables having the strongest impact (Additional figures in Annex 3). However, one interesting difference can be observed. Inclusion of the transport variable did have a significant added value with respect to reduction in the relative risk (Figure 9). This suggests that when dengue is not in its epidemic phase and spread widely across the city, khwaeng connectivity can play a role in the creation of dengue hotspots; the more connected a khwaeng is, the higher is the relative risk.

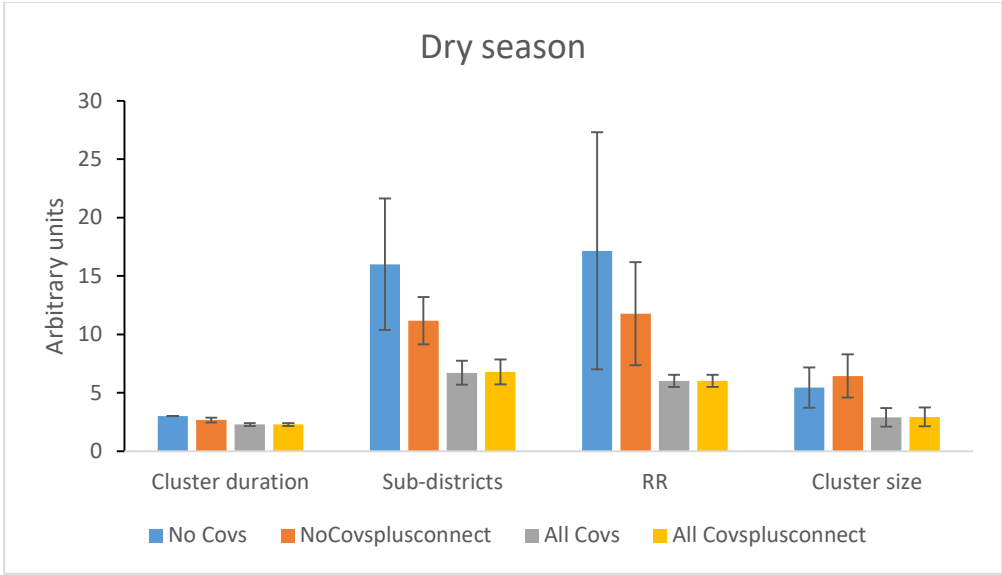


Figure 8: Summary of the Spatio- temporal hotspots analyses during the dry season

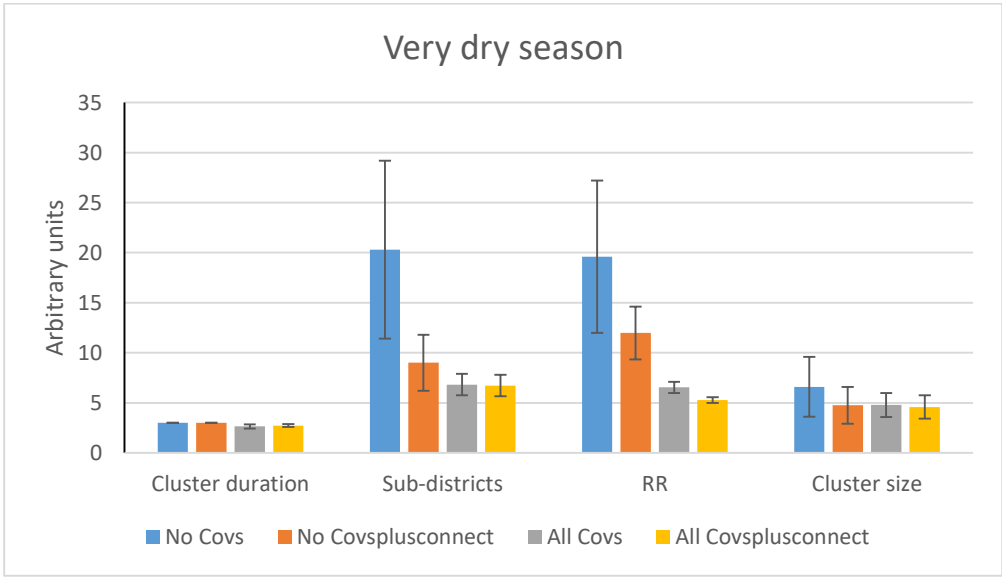


Figure 9: Summary of the Spatio- temporal hotspots analyses during the very dry season

Although the association of number of transport stops per khwaeng was of relatively minor importance, analysis of the impact of the transport system should include number of connections from one khwaeng to the others, rather than just a general number. With this in mind, understanding how the population and the transport network is structured in Bangkok can help in assessing the effect of human mobility on dengue incidence.

4.3. Spatial description of transport network

The databases used are meant to offer a global overview of global population distribution and allow for comparison. However, we noticed some strong variation from database to another regarding the population counts in each cell. We compared the population counts retrieved from the cells of GPW in 2010 and 2015 and LandScan from 2012 and 2017 databases after aggregating them with the NSO figures for the Khwaengs and Khets for 2010 to see if we have a lot of discrepancy and to better assess how the population counts per cell are computed (Figure 10). Assessing the global population distribution is important to better link it with the transport network repartition and therefore human mobility.

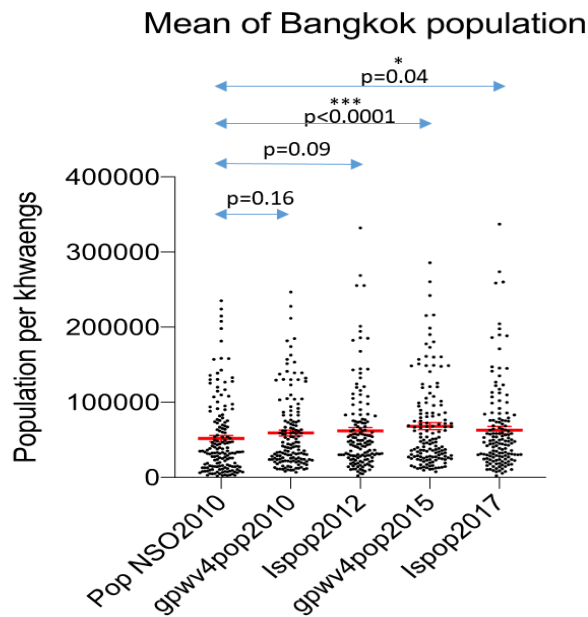


Figure 10: Comparison of the population counts using GPW and LandScan with NSO 2010

To better visualize the population density, we mapped it on QGIS with LandScan 2012 database as an example. The population is concentrated in the center along the Chao Phraya river where there is more public transportation (Figure 11).

Population density in BMA using LandScan 2012

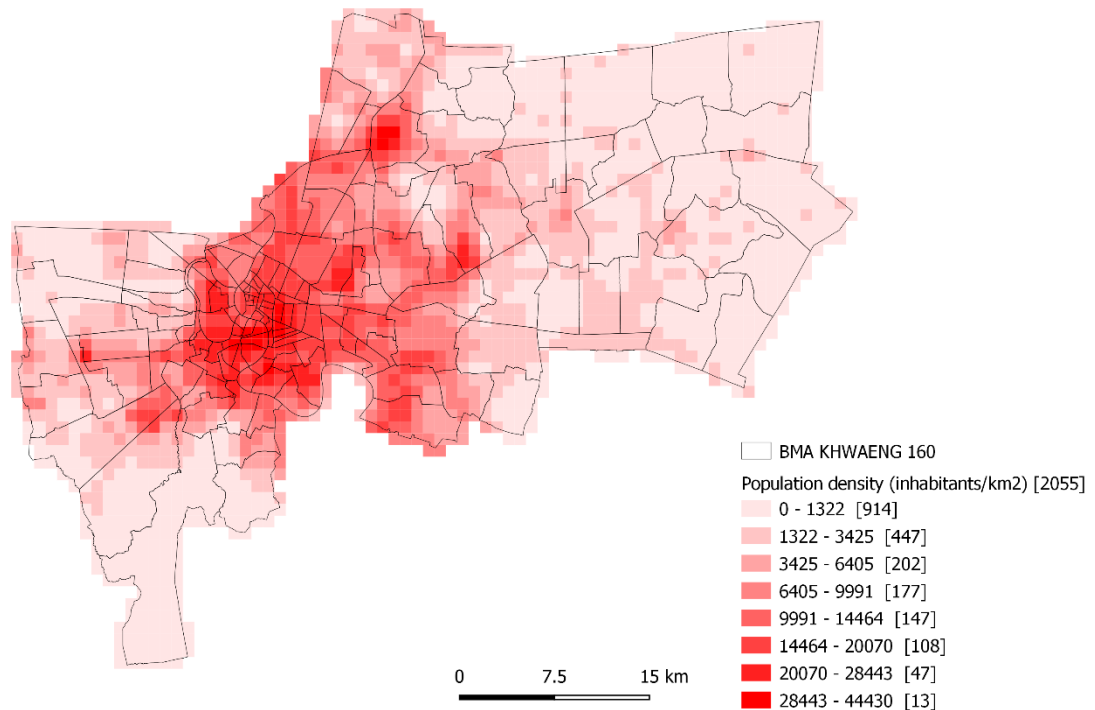


Figure 11: Mapping of the population density with LandScan 2012 database

As a result of the spatial analysis, 4,223,025 trips were computed and extracted to a CSV file. They were then aggregated into OD matrixes for Khet and Khwaeng administrative units.

A specific problem arose, while aggregating trips results from the barycentres into an OD matrix for the khwaengs (N=160). Because some khwaengs in the city center are small or have very specific shape, it was impossible to link 15 khwaengs to any barycentre based on their location. Returning to the cells extent and the khwaeng's polygonal extent, we selected barycentre results to calculate the average distances and the number trips linking these 15 khwaengs to all the other khwaengs and between them. We used a series of tools in Excel (Power Query, Pivot Table) to retrieve and reaggregate the results from 26 barycentres for the 15 khwaengs. Some manual check-up was also performed to check discrepancies. Some barycentres results have been used for several khwaengs, leading the number of trips being computed to build the khwaeng OD matrix to reach 4,437,428 (as compared to the 4,223,025 trips initially computed with QNEAT). While aggregating the results, it was possible to compute the distance and trips between barycentres within each khwaeng, except for 17 of them. Most of them are located in the city

center and because of their size and shape they have only a single barycentre to compute the distance from.

The average distance from one central and one peripheral khwaeng to the other khwaengs are visualized in the figures 12 and 13 below.

This OD matrix will form the basis of future spatial regression analyses to further tease out the role of human mobility in the spatio-temporal distribution of dengue within the city.

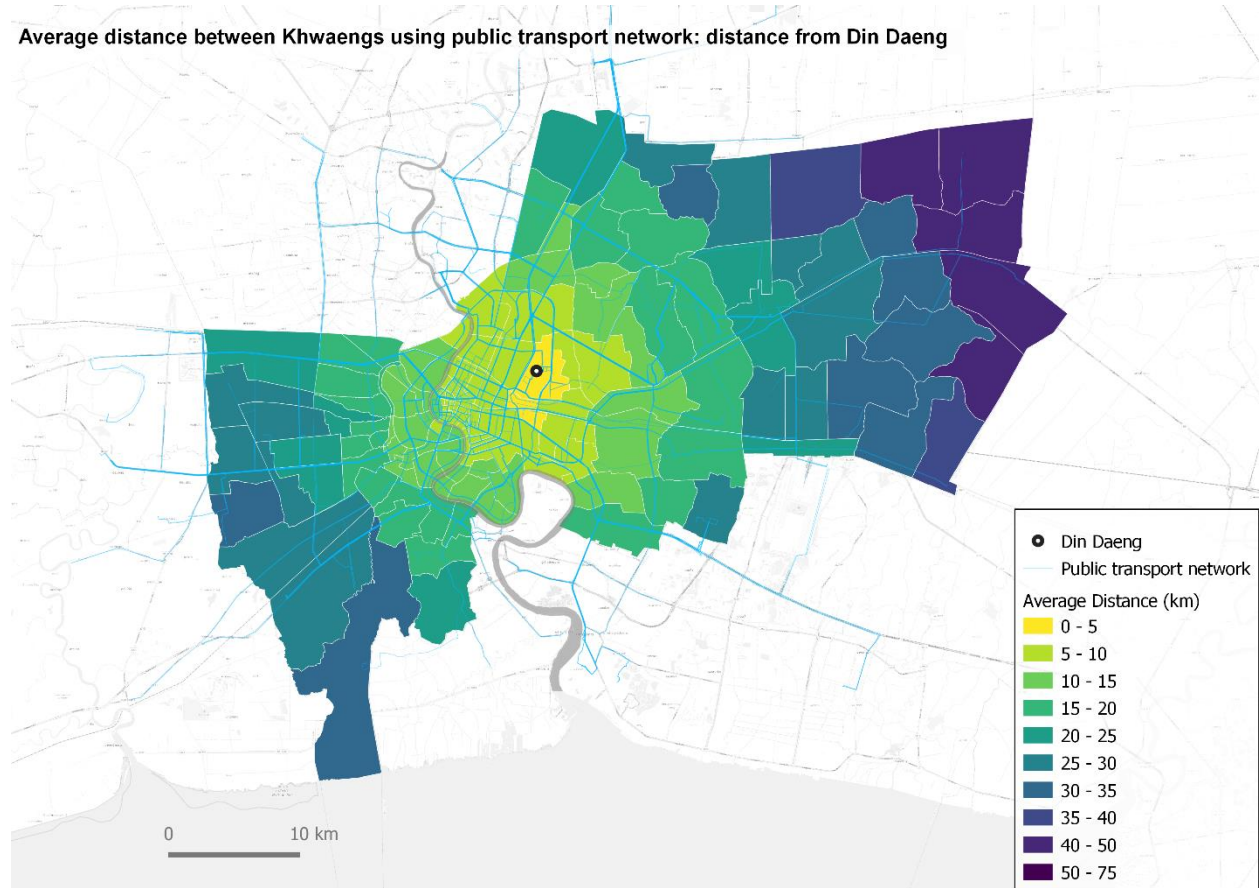


Figure 12: Average distance from Din Daeng using public transport network

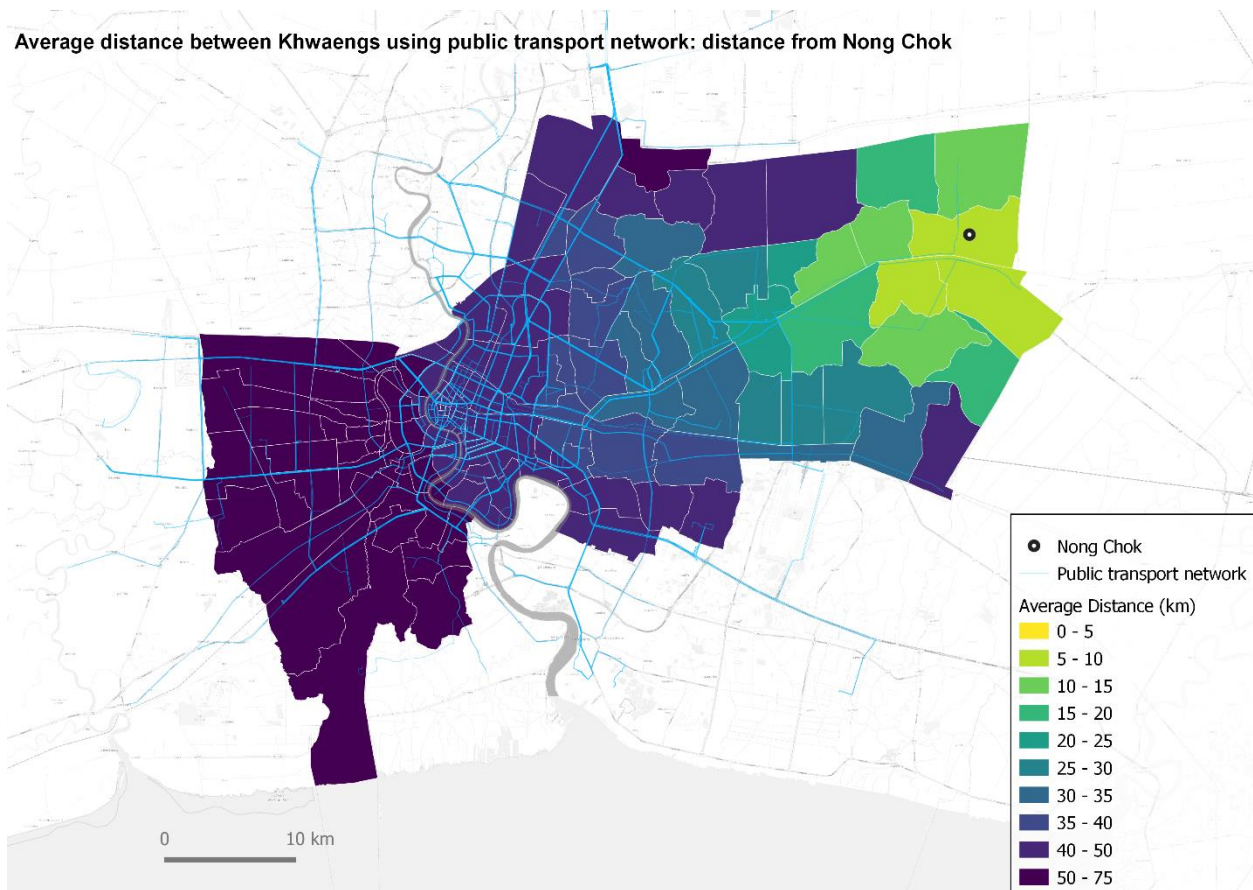


Figure 13: Average distance from Nong Chok using public transport network

5. Discussion and implication with Public Health

This study attempted to understand the impact of some socio-economic variables and number of connections in the transport network with dengue incidence in the urban setting of Bangkok. The sample size was just over 25,000 for the main study period (2012- 2013). The association was tested at the lowest administrative unit in Bangkok, khwaeng level. This has helped in providing a deeper understanding of the human mobility and distribution of dengue and areas of elevated risk across Bangkok over two years.

In the city center of Bangkok, where the number of transport, mobility, human activity and density is higher, there was an increase in dengue cases. This finding is coherent with the previous study in Guangzhou city, China where high road density was found to be a risk factor for clinical dengue (22). However, the relationship between transport and dengue incidence remains poorly studied. In lower population density areas, chances of dengue transmission are lower due to the short flight range of the

mosquito. Seasonality also has a strong role in dengue transmission in endemic settings and in our study, when seasons were analyzed separately, khwaeng connectivity played a role in the creation of dengue hotspots; the more connected a khwaeng was, the higher the relative risk.

A high percentage of lack of education also found to be a risk factor, likely reflecting poor income as well as lack of knowledge on personal protection and environmental hygiene; raising the question of whether dengue is a disease of poverty.

The OD matrix generated will help to assess the extent to which its inclusion can improve the explanatory power of meteorological and socio-economic variables previously shown to be associated with dengue incidence through future spatial regression analyses.

Our study has some limitations. One of them is the fact that surveillance data are subjected to bias of under or over reporting as they only cover clinically apparent cases. This study that used aggregated variables at khwaeng level does not account for individual risk factors. Moreover, if the data are available, using individually geolocated dengue cases can improve the analysis as this bypasses the need to convert network characteristics into attributes of an administrative area. Additional data could also be used to assess daily commuting such as the Social Connectedness Index from Facebook, Call Detail Records, tweets or other social media (13, 30). In fact, in the recent years, our world has become hyper connected due to the advancement in the technology and the extensive use of mobile phones. Social media has contributed to measure human mobility within and between cities by deriving quantitative measures at useful spatial scales. Call detail records are collected by operators and give information on an individual's movement to the closest telephone tower. These capture the major components of human mobility: the total trip distance, the characteristic distance travelled by a person and the number of sites visited. Aggregated across a population, these data can reveal important features of larger scale movement patterns and how the distribution of the components alters over time and place. As a very recent example, there is currently discussion on the use of social media data to capture the impact of lockdown on human mobility to guide the public health response to Covid-19 (31). Aggregated, anonymized, passively collected mobile phone data have also been previously used in infectious disease modelling of dengue. A study done in Pakistan showed that mobile phone-based mobility estimates helped to foresee the geographic spread and timing of epidemics in both new dengue epidemic and emerging locations (32). These data can help assess how changes in mobility contribute to the spread of infectious diseases. Incorporating such information into models will improve our capacity to identify sources and pathways of the spread of infection. This will eventually enable a much more targeted approach for implementing preparedness plans and interventions.

In addition, the analysis can be improved if time-series data of greater than 2 years can be used. Potential biases had to be considered as well regarding the evolution of the public transport network (data collected for 2018) against OSM road network information and variables collected for 2012-13.

Finally, the public transport system network used in this study does not account for all urban mobilities such as the use of cars and tuk tuk that comprise a big part of the transport network.

Today, no vaccine or specific therapy exists to treat DENV; therefore, disease control has focused on measures to control the mosquito vector. However, in a country like Thailand where outbreak occurs every few years, there is a clear need to also improve disease control strategies with active surveillance and community awareness. Fortunately, in a very recent study, the deployment of a bacteria, *Wolbachia* in infected mosquito with dengue in Indonesia have proved efficacy for the control of dengue: the incidence of symptomatic dengue was reduced and fewer hospitalizations were noted among the participants. This approach of introgression represents a new and more efficient strategy for the control of dengue since it is maintained in the mosquito population over generations and does not need reapplication. More studies and trials are needed to assess the efficacy for other infectious diseases caused by *Ae. aegypti* such as Zika, chikungunya and yellow fever (33).

Option for future analysis would be to look at Arcgis Pro Network Analyst and build a full General Transit Feed Specification (GTFS) database in association with OpenStreetMap road network. The GTFS would be interesting because it includes a static component that contains schedule, fare, and geographic transit information and a real time section that covers arrival predictions, vehicle positions and service advisories. In order to do so, we would need to return to original files collected from OSM and TransitBangkok to include more data on public transport routes (timing, out/in-bound directions...) and compute more detailed service areas in relation to the location of entry/exit points to bus, ferry and metro lines.

On a more Public Health perspective, the COVID-19 pandemic is placing immense pressure on health care and management systems everywhere in the world and specially in urbanized areas and tropical countries such as Thailand. Urban populations are exposed at highest risk for both diseases. The combined impact of COVID-19 and dengue epidemics can potentially result in devastating consequences on the populations at risk. During this crucial period, WHO has emphasized on the importance of sustaining efforts to solve this threat via multi-sector strategies and public health policy to prevent, detect and treat vector-borne diseases such as dengue and other arboviral diseases, as case numbers increase in several countries (1).

6. Conclusion

It is only relatively recently that the spatial sub-structure of dengue epidemiology is being considered as an important determinant in dengue epidemiology at different scales. The findings of this study provide some insights into some socioeconomic risk factors and the spatial pattern in disease occurrence in a hyperendemic setting. There were significant lagged correlations in dengue incidence rate between khwaeng, suggesting that connectivity may play a role in the spatial distribution of dengue. In addition to the clear significant impact of several socio-economic risk factors associated with dengue in the spatial analyses, general khwaeng connectivity did make a significant contribution to the dengue hotspots and particularly so during the very dry season. This may reflect the fact that during the rainy season dengue is already widely spread and thus population mobility is of lesser importance in spreading the virus. A more detailed analysis using the actual mobility patterns at varying times of year would be of value.

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Annexes

Annex 1: Results of the CCF between the 18 selected khwaengs

khwaeng	100107	100701	100101	102501	101204	101602	105501	103004	103302	101106	100301	100303	105203	104902	102105	104802	102302	102901
100107		31.29/-4/0.659	10.08/-3/5.61	21.67/-4/0.59	18.4/-3/0.48	25.5/-4/0.64	17.5/-3/0.72	1.15/+1/-0.26	2.58/0/0.357	27.4/-3/0.722	11.98/+1/0.559	11.69/-4/0.564	0.78/+4/0.40	12.4/-1/0.525	22.3/-3/0.625	8.64/-2/0.51	8.52/-3/0.375	2.53/-1/0.268
100701			5.28/+1/0.784	14.1/0/0.858	10.96/0/0.826	5.53/0/0.735	5.49/0/0.816	5.26/-1/0.324	3.89/0/0.584	22.6/-2/0.658	8.39/-2/0.488	10.2/-1/0.54	6.44/-1/0.31	15.7/0/0.699	2.64/+2/0.66	6.89/+1/0.52	1.93/0/0.44	
100101				13.5/-1/0.672	9.37/0/0.728	6.1/0/0.7	2.08/+1/0.754	1.99/-2/0.203	9.03/-1/0.572	11.64/0/0.474	5.08/+1/0.273	8.49/-2/0.499	3.08/-2/0.374	8.43/0/0.76	6.03/0/0.529	0.28/+1/0.737	2.7/0/0.32	1.75/+1/0.265
102501					7.88/0/0.747			6.3/-1/0.357	3.41/0/0.666	15.65/+1/0.577	6.06/+2/0.468	4.73/0/0.4736	11.75/-1/0.473	8.45/0/0.756	8.37/0/0.686	2.64/+2/0.598	3.32/0/0.586	5.68/0/0.499
101204						5.3/+1/0.669	7.19/0/0.763	10.95/-1/0.465	0.6/0/0.693	16.4/0/0.562	8.11/-1/0.394	9.17/-1/0.443	10.6/-2/0.4465	11.63/0/0.773	13.28/0/0.714	1.26/+1/0.773	7.78/-1/0.513	27/0/0.549
101602							11.81/0/0.748	5.18/-1/0.341	4.5/0/0.448	20.73/0/0.671	7.88/-1/0.488	8.38/-1/0.377	5.97/-2/0.352	10.31/0/0.679	17.58/0/0.73	9.02/0/0.5715	6.755/0/0.626	4.61/0/0.591
103501								7.42/-3/0.3587	2.3/0/0.567	20.03/-2/0.589	6.28/0/0.359	7.64/-1/0.449	8.11/-2/0.373	14.47/-1/0.6325	14.31/0/0.6399	3.06/+1/0.476	6.04/0/0.532	3.96/0/0.448
103004									3.94/0/0.457	4.05/+1/0.2	2.49/0/0.236	2.33/0/0.213	28.73/-2/0.617	3.41/+1/0.723	1.48/+2/0.488	6.78/+1/0.598	8.88/+1/0.763	
103302										5.54/-3/0.367	7.48/0/0.392	3.83/+2/0.33	16.91/-2/0.561	5.85/0/0.688	4.73/0/0.444	2.5/+2/0.649	7.19/+2/0.397	4.29/0/0.568
101106											4.75/+1/0.456	7.19/+1/0.48	2.49/-2/0.235	7.57/+1/0.577	10.46/0/0.684	4.38/+1/0.529	5.13/0/0.433	4.47/0/0.26
100301												3.37/0/0.454	5.61/-2/0.286	6.88/-2/0.48	10.83/-1/0.463	6.89/0/0.403	8.09/-1/0.494	4.55/0/0.343
100303													2.68/-4/0.234	1.14/+3/0.38	4.29/0/0.452	0.79/+3/0.358	3.86/0/0.551	1.52/-3/0.177
103203														4.88/+2/0.551	11.86/+2/0.473	3.63/+3/0.427	4.65/+2/0.615	4.91/+2/0.70
104902															14.86/0/0.672	4.82/0/0.618	13.28/0/0.661	11.14/0/0.781
102105																6.42/0/0.604	8.23/0/0.796	7.98/0/0.521
104802																	5.6/0/0.675	10.44/-1/0.557
102302																		16.76/-1/0.709
102901																		

Annex 2: Summary of the spatio- temporal hotspots analyses

During 2012 and 2013 independent of season

	Cluster duration	Sub-districts	RR	Cluster size
No Covs	3	18.25	11.97	5.5
NoCovsplusconnect.	3	12.5	6.92	3.5
All Covs	2.54	7.23	3.03	3.9
All Covsplusconnect	2.83	7.17	2.93	3.64
SEM (standard error of the mean)				
No Covs	0	6.64	5.99	2.36
NoCovsplusconnect.	0	2.29	2.99	0.57
All Covs	0.18	0.78	0.24	0.93
All Covsplusconnect	0.11	0.86	0.28	0.82

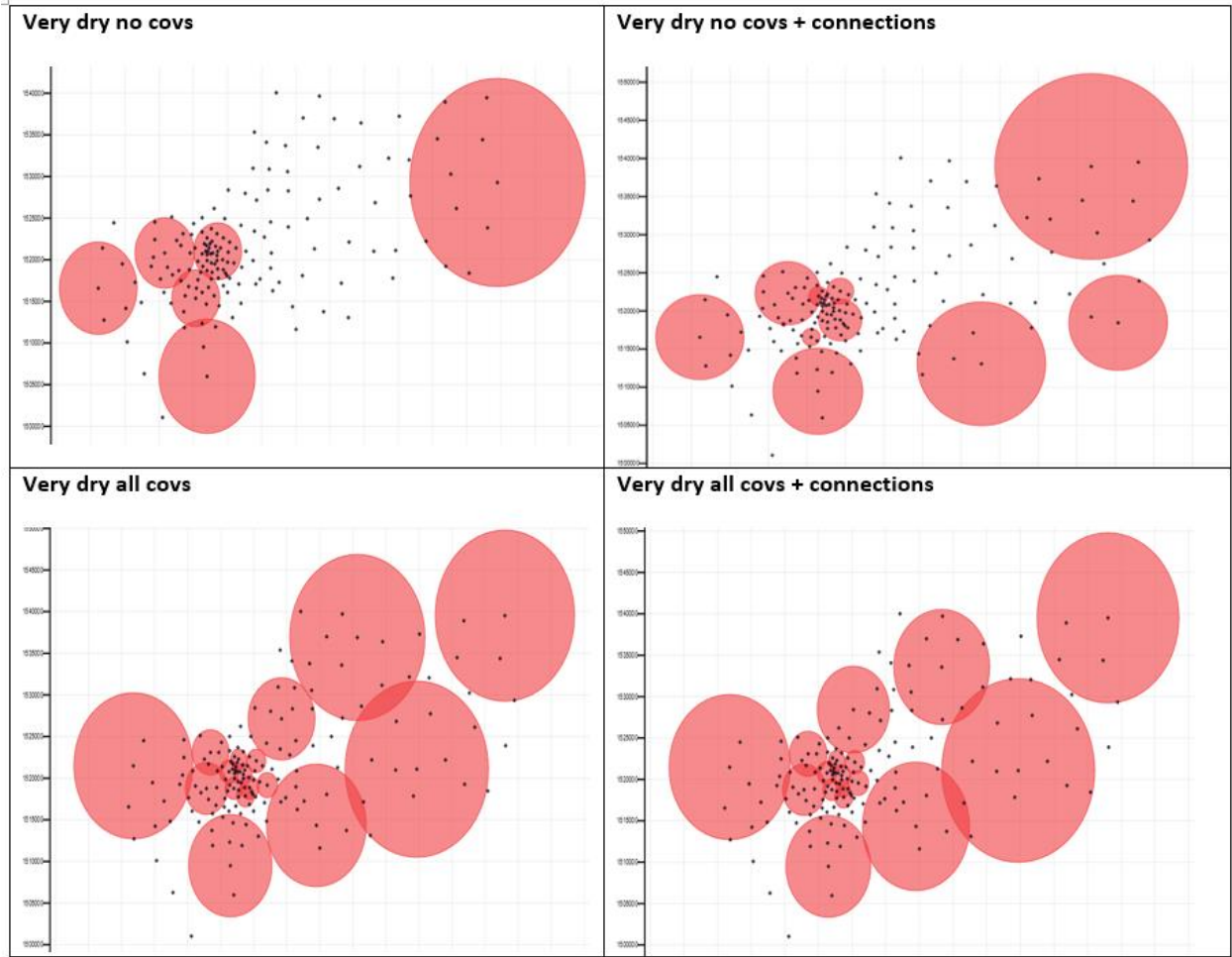
During dry seasons

	Cluster duration	Sub-districts	RR	Cluster size
No Covs	3	16	17.2	5.44
NoCovsplusconnect.	2.7	11.2	11.77	6.43
All Covs	2.3	6.7	6.02	2.9
All Covsplusconnect	2.3	6.8	6.01	2.93
SEM				
No Covs	0	5.6	10.2	1.73
NoCovsplusconnect.	0.21	2.0	4.42	1.85
All Covs	0.13	1.0	0.52	0.8
All Covsplusconnect	0.13	1.06	0.52	0.81

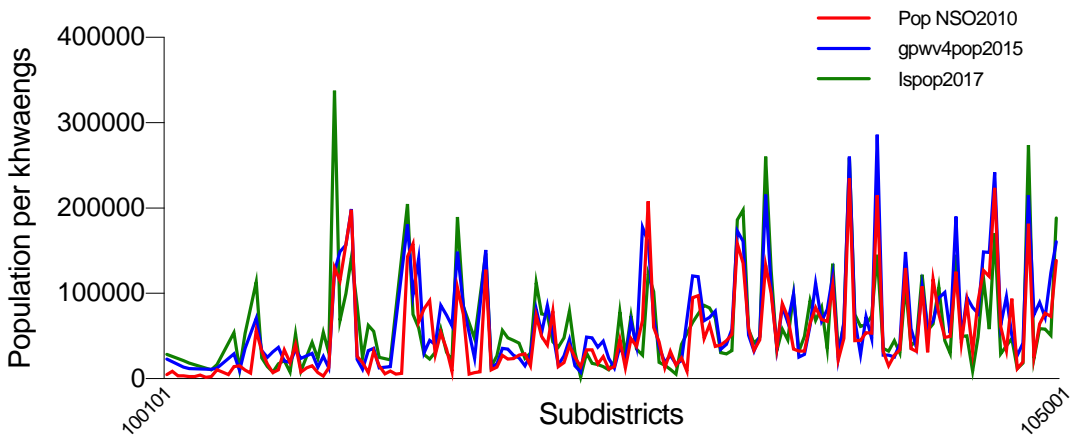
During dry season excluding months 12 to 14 and 24

	Cluster duration	Sub-districts	RR	Cluster size
No Covs	3	20.3	19.6	6.598
NoCovsplusconnect.	3	9	11.98	4.75
All Covs	2.6	6.8	6.55	4.78
All Covsplusconnect	2.7	6.7	5.27	4.58
SEM				
No Covs	0	8.88	7.61	2.998
NoCovsplusconnect.	0	2.8	2.64	1.85
All Covs	0.2	1.07	0.56	1.21
All Covsplusconnect	0.14	1.07	0.29	1.16

Annex 3: Dengue case hotspots detected through SaTScan analyses during the very dry season

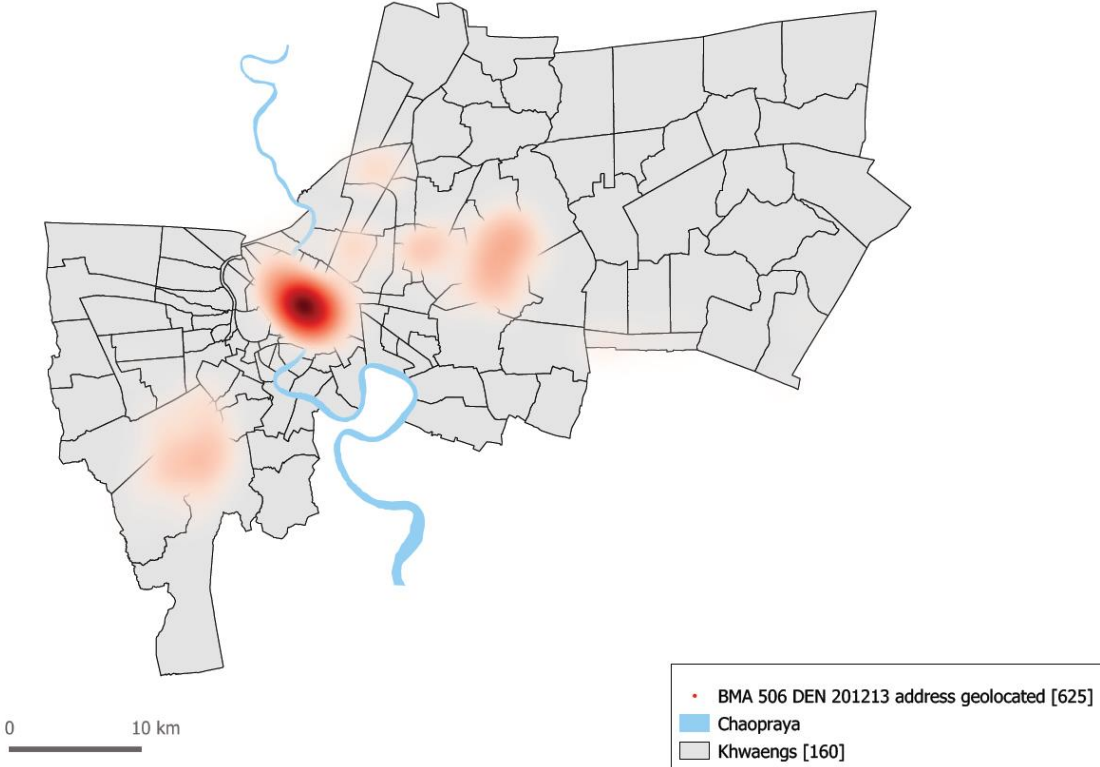


Annex 4: Comparison of the distribution of the population in the khwaengs with NSO 2010 and the 2 datasets GPW 2015 and Landscan 2017 that have statistical significance



Annex 5: Heatmap representing 625 geolocated dengue cases in Bangkok during 2012 and 2013

Dengue Incidence 2012- 2013



Annex 6: Average and Median distance between Khwaengs using public transport network

