Large Scale Detailed Mapping of Dengue Vector Breeding Sites Using Street View Images

Peter Haddawy[1,2], Poom Wettayakorn[1], Anuwat Wiratsudakul[3], Johannes Schöning[4], Yongjua Laosiritaworn[5], Boonpakorn Nonthaleerak[1], Klestia Balla[6], Sirinut Euaungkanakul[1], Papichaya Quengdaeng[1], Kittipop Choknitipakin[1], Siripong Traivijitkhun[1], Benyarut Erawan[1], Thansuda Kraisang[1]

[1] Faculty of ICT, Mahidol University, Salaya, Thailand

[2] Bremen Spatial Cognition Center, University of Bremen, Bremen, Germany

[3] Faculty of Veterinary Science, Mahidol University, Salaya, Thailand

[4] University of Bremen, Bremen, Germany

[5] Ministry of Public Health, Bangkok, Thailand

[6] Computer Science Department, School of Science and Technology, University of Camerino, Camerino, Italy

Abstract

Targeted environmental and ecosystem management remain crucial in control of dengue. But providing detailed environmental information on a large scale to effectively target dengue control efforts remains a challenge. In this paper we present the design and implementation of a pipeline to detect potential dengue vector breeding sites from geotagged images to create highly detailed container density maps at unprecedented scale. We implement the approach using Google Street View images which have the advantage of broad coverage and of being somewhat historical so that the data can be aligned with other types of data for analysis. Containers comprising eight of the most common breeding sites are detected in the images using convolutional neural network transfer learning. Over a test set of images the object recognition algorithm has an accuracy of 0.91 in terms of F-score. Container density counts are generated and displayed on a decision support dashboard.

Extensive analyses of the approach is carried out over three provinces in Thailand. Results show that the container density counts agree well with manual container counts, with larval survey data, and with dengue case data. To delineate conditions under which the density counts are indicative of risk, a number of factors affecting agreement with larval survey and dengue case data are analyzed. We conclude that creation of container density maps from geotagged images is a promising approach to providing detailed risk maps at large scale. Ultimately, we intended to include our newly proposed index in the identification of dengue high-risk areas in Thailand.

Introduction

Dengue is considered one of the most important mosquito-borne viral diseases in the world. During the past five decades, the incidence of dengue has increased 30-fold, with a recent study estimating global incidence at 390 million cases per year [1]. Dengue is now considered endemic in more than 100 countries, with more than two thirds of the burden found in Asia. Even in Europe, an outbreak on Madeira that began in 2012 resulted in over 2,000 cases, with imported cases from travelers to Madeira detected in 13 other European countries [2].

The *Aedes aegypti* and *Aedes albopictus* mosquitoes are the primary vectors of dengue and are additionally responsible for the spread of chikungunya, Zika fever, and yellow fever [3]. The *Aedes* mosquitoes have adapted to human habitats and breed in relatively small containers that can hold water such as ceramic jars, old tires, flower pots, and buckets. Studies of the dispersal of *Aedes aegypti* and *Aedes albopictus* indicate that the mosquitoes are capable of active dispersal over only short ranges [4] [5] [6]. The combination of small scale breeding sites and low level of mobility of the vector results in highly localized sites of disease transmission with dengue exhibiting substantial geographic variability [7] which makes accurate disease risk mapping a significant challenge.

One dengue vaccine (CYD-TDV or Dengvaxia) has now been registered in several countries. But with about 60% effectiveness and lack of approval for use in children under 9 years old, it does not provide an effective line of defense [8]. Since there is also no curative treatment for dengue, targeted environmental and ecosystem management continue to be crucial in controlling the disease.

Two primary approaches have been taken to providing environmental data for dengue risk mapping and prediction. The first is to use remote sensing [9] or proxies [10] to assess local environmental conditions [11]. These approaches do not provide the detailed information about breeding sites needed to help guide intervention. A second approach is to carry out manual surveys in which containers with water or containers with water and larvae are counted. Results are then reported in terms of numbers of containers of different types or in terms of larval indices: Breteau Index, House Index, and Container Index [12] [13]. This can provide sufficient resolution, but is not scalable due to its labor-intensive nature. Thus, there is a need for an approach that can provide information on potential breeding sites at sufficiently high resolution and that is scalable to cover major cities and provinces, the scale needed to support control efforts.

In this study, we address this problem by using convolutional neural networks (CNN) to detect a variety of types of breeding site container types in geotagged images and use the container counts to create risk maps. While our architecture can accommodate geotagged images from a wide variety of sources, in this study we use Google Street View (GSV) images due to the extensive geographic coverage and the historical nature of much of the image data, which allows it to be temporally aligned with larval survey data and dengue incidence data for evaluation. Extensive evaluation of the approach is carried out over three provinces in Thailand: Bangkok, Krabi, and Nakhon Si Thammarat. Our evaluation shows that the object recognition network can accurately recognize several of the most important types of containers in Thailand. We further show that simple multi-linear models using container density values provide good predictions of Breteau index values and provide weak to moderate quality predictions of dengue incidence. This is the first study to present results validating breeding site counts from image analysis against such data.

Related Work

In their review of dengue risk mapping modeling tools, Louis et al. [14] showed that social predictors such as education level, occupational status, and income are often used as proxies to assess local environmental conditions and hygiene, which are normally difficult to assess directly. Housing conditions are often used as a proxy to assess type and amount of mosquito breeding sites. Access to running water has also been found to be a risk factor for dengue since residents in such areas tend to store water in ground-level containers [15] [16]. Chang et al. [17] used satellite imagery from Google Earth to create a base map to which they added information about indices of larval infestation, locations of tire dumps, cemeteries, large areas of standing water, and locations of homes of dengue cases, all of which were collected manually. They found the resulting system allowed public health workers to prioritize control strategies and target interventions to highest risk areas.

A number of researchers have developed applications for reporting or detecting mosquito breeding sites, as well as other information related to dengue outbreaks. Agrawal et al. [18] use a support vector machine and scale-invariant feature transform (SIFT) generated features to classify individual images as being breeding sites or not. Their approach relies on users to take photos of individual sites. On a test set of 78 images they achieved a binary classification accuracy of 82%. Mehra et al. [19] present a technique for identifying stagnant water bodies in images. Using an ensemble of naive Bayes classifiers and boosting they achieve a binary classification accuracy of 90%. Quadri et al. [20] present TargetZika, a smartphone application for citizens to report breeding sites using photos and descriptions. They provide no automated classification of the photos but rather rely on users to label them from a menu. They use the data to produce risk maps but do not validate them. Mosquito Alert [21] is a similar smartphone application that allows users to report breeding sites and mosquitos with photos and descriptions. It uses crowdsourcing to identify photos. Reports are displayed on a map on the Mosquito Alert website.

Some researchers have manually extracted features from GSV data for environmental monitoring purposes. Rundle et al. [22] manually extracted features from street view data to audit neighborhood environments and compared the results to field audits. They found a high level of concordance for features that are not temporally variable. Rousselet et al. [23] manually extracted species occurrence data for the pine processionary moth from GSV images and compared the results to field data. The two were found to be highly similar.

Runge et al. [24] made use of the scene recognition convolutional neural net of Zhou et al. [25] to label GSV images and assembled them into maps to find scenic routes for autonomous vehicle navigation. Although their application differs from ours, their pipeline and the structure of their feature maps are similar to those in this study. Since we are interested in obtaining counts of numbers of breeding sites in a given region, in this study we make use of object detection networks. Recently, region proposal methods have yielded the highest performance in object detection [26]. Region proposal methods first hypothesize regions that may contain objects of interest and then use CNNs to identify objects in those regions. Girshick [27] introduced Fast Region-based Convolutional Neural Networks (Fast R-CNN) which reduced the running time of the detection network, making the region proposal computation the bottleneck. Recently, Ren et al. [28] introduced Faster R-CNN, which greatly improves the computational efficiency. By sharing convolutional features between the regional proposal and detection networks, they reduce the computational cost of region proposal to near zero and achieve a frame rate of 5 frames per second on a GPU.

Methods

We describe details of the three main components of our pipeline to detect and map containers in geotagged images, namely image retrieval, object detection, and data visualization.

Data Collection Process

The region from which to retrieve images is defined using a GeoJSON file (Figure 1 (left)). The first step is to generate points within the region from which to retrieve the GSV images. This is done by obtaining the polylines of each road from the Openstreetmap Overpass API [29] (Figure 1 (middle)) and then plotting points along the roads at 50 meter increments (Figure 1 (right)). A distance of 50 meters gives complete image coverage without overlap.

Figure 1. GeoJSON (left), road polylines (middle), and generated points along roads (right).

Map data (left, middle) © Mapbox, © OpenStreetMap; map data (right) © 2018 Google, Krabi.

With the points defined, images are downloaded using the GSV API [30]. Since the API does not support retrieving the entire 360-degree scene as one image, five images are retrieved 72 degrees apart and at a field of view (FOV) of 75 and a pitch of -15 degrees (Figure 2). Each image has resolution 640 × 500 pixels. In addition, the metadata for each image is retrieved, consisting of the geo-coordinate and the year and month the image was taken.

Figure 2. Example of a set of retrieved images from Google Street View

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Container Detection

Dengue vector breeding sites consist of open containers of varying size that can contain water. The frequency of occurrence and the suitability of containers as breeding sites varies, with ceramic containers generally more suitable than plastic containers. While the importance of particular types of containers as breeding sites varies from country to country and even among geographic regions in a country [31], analysis of the research literature [32] [33] [34] [35] as well as publications of the Ministry of Public Health of Thailand [36] [37] revealed six container types that were consistently important across regions. These are large ceramic jars, buckets, old tires, potted plants, bins, and bowls, as shown in Figure 3. This list was confirmed through consultation with local entomologists. In general, large ceramic jars are the most important container type [36] [32], being commonly used to store water near homes, particularly in rural areas.

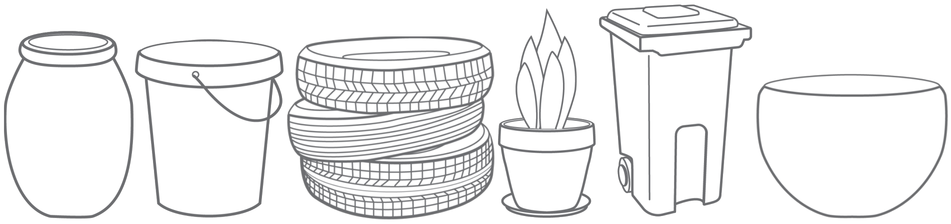


Figure 3. Common dengue vector breeding sites in Thailand (from left to right): large jar, bucket, old tire, potted plant, bin, ceramic bowl.

Smaller containers such as bottles and cans are also possible breeding sites but are too small to detect in GSV images with high accuracy. While some areas such as construction sites, garbage dumps, and empty lots are commonly considered potential breeding sites [13] [38], they are considered so because they tend to house open containers and are not the focus of this study. They can be detected using scene recognition techniques [25], like those used in the work of Runge et al. [24].

Finding containers in GSV images falls into the class of problems know of as object detection. We do this using Faster R-CNN of Ren et al. [28] which has state-of-the-art runtime performance. To implement the Faster R-CNN network, we use TensorFlow which includes a number of architectural variations on Faster R-CNN that trade accuracy for speed and memory usage [39]. We use the architecture of Faster R-CNN with ResNet-101 which has close to the highest accuracy on the Microsoft COCO object detection dataset [40] yet still excellent runtime performance (2-3 times as fast on our dataset as the highest accuracy Faster R-CNN with Inception and ResNet). Performing object detection on the close to 1 million images for the province of Nakhon Si Thammarat in Thailand took 95 hours of processing time on a PC with a 3.6GHz i7-7700 processor, 32 GB RAM, and a 1080 Ti graphics card.

Faster R-CNN includes the object categories bucket, potted plant, and bowl, but does not include object categories for large jar, bin, and old tire. We thus used transfer learning to detect these categories [41]. This was done by replacing the entire output layer of Faster R-CNN with our desired set of object categories, three of which were new and the remainder of which had been in the original Faster R-CNN, as shown in Figure 4. This network was then trained with the training data for all categories. Since a large variety of container types can be potential breeding sites, in addition to these six categories, we added categories for misc short open container and misc long open container using existing categories in Faster R-CNN, resulting in a total of eight categories.

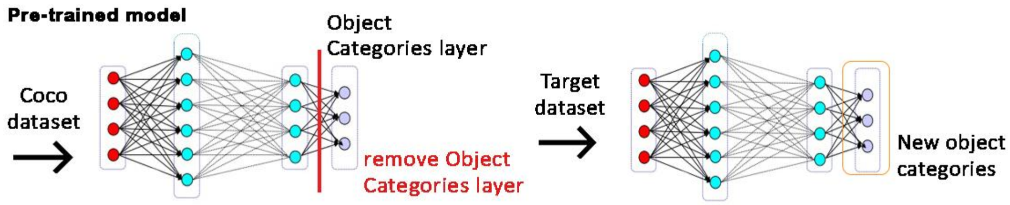


Figure 4. Performing transfer learning on pre-trained model by replacing output layer with new target classes.

A training set of five thousand images was assembled from the COCO dataset [42], GSV images from Bangkok, and Google image search on Thai language strings describing the container types. All containers in the images were manually annotated with bounding boxes and container type labels by using the LabelImg [43] tool. Since each image can contain more than one container object, the collected images contained a total 8,653 containers: 2,318 old tires, 1,110 large jars, 1,385 buckets, 2,758 potted plants, 135 bins and 947 bowls. Distinguishing a discarded old tire from a tire attached to a vehicle is difficult, so we solved this problem by adding vehicle as an object category and eliminating tires that have bounding boxes that substantially overlap with the bounding box of a vehicle. The dataset was randomly split into 90% for training and 10% for testing. Figure 5 shows examples of detected containers in GSV images using the network resulting from transfer learning.

Figure 5. Examples of detected containers in Google street view images by using Faster R-CNN with new transferred categories. Original images © 2018 Google, Chatuchak, Bangkok

Data Visualization Dashboard

The dashboard, shown in Figure 6, provides visualization of the various data relevant to dengue risk, including container density, dengue incidence, Breteau index, population demographics, rainfall, and temperature. The data is displayed in terms of choropleth maps and graphs using MapBox JS [32]. The maps are created by using a GeoJSON file as input and then applying a data-driven styling approach. Three charts are visible on the right side of the dashboard. The first chart displays statistics for the entire province while the other two charts display statistics for the selected sub-district. Users can filter the data to display only a certain year or season. Similarly, users can filter containers to display data for only certain types of containers. Each map has an additional mouse hover overlay where the exact value of the variable is shown.

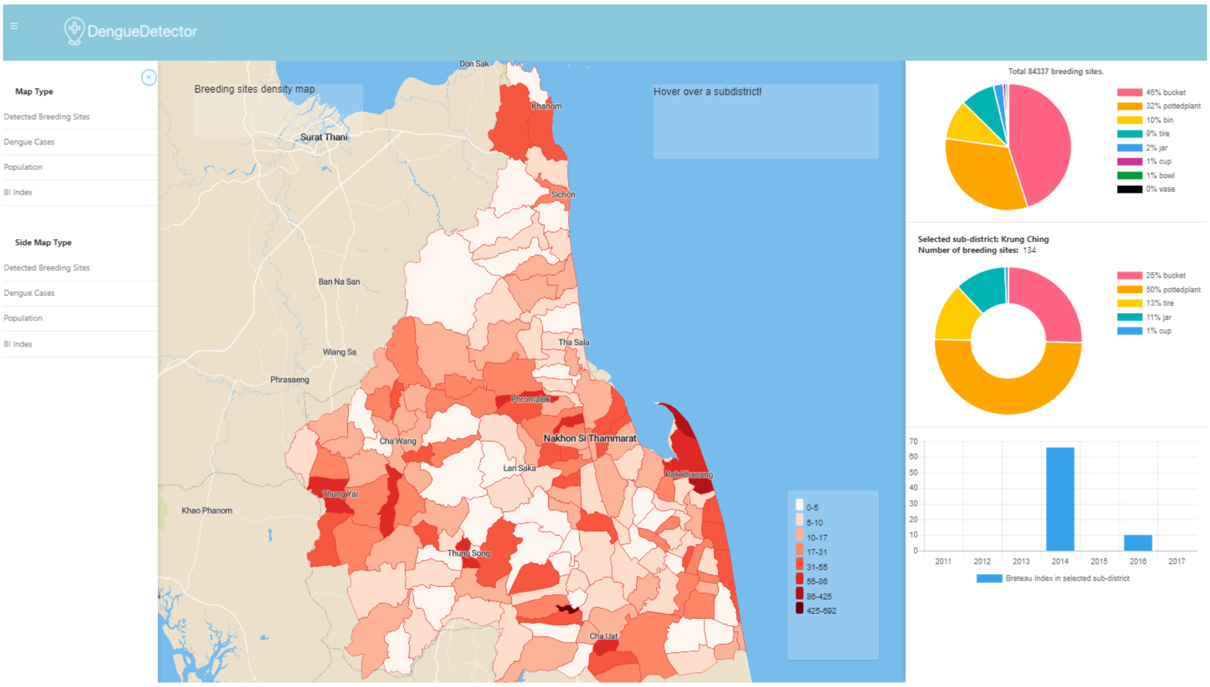


Figure 6. Information visualization dashboard. The choropleth map displays container densities for all sub-districts in Nakhon Si Thammarat province. The top chart on the right shows relative percentages of container types in the whole province. The second and third charts show statistics for the selected sub-district, in this case Krung Ching. When hovering over a subdistrict the data for the subdistrict is displayed. Map data © Mapbox, © OpenStreetMap.

Results and Discussion

In this section, we evaluate the accuracy and value of container counts obtained from our automated analysis of GSV images by carrying out four types of analyses. We first evaluate the accuracy of the object recognition technique in detecting containers in GSV images. We then present detailed statistics on container counts over three provinces in Thailand: Bangkok, Krabi, and Nakhon Si Thammarat. Subsequently, we evaluate the correspondence between container density counts and Breteau index values from manual surveys in Nakhon Si Thammarat. Finally, we evaluate the correspondence between container density counts and dengue incidence over the three provinces. Krabi province was chosen because it consistently has one of the highest dengue incidences in

Thailand. Nakhon Si Thammarat was chosen because it has the greatest availability of manual larval survey data. Bangkok was chosen because, as the most urbanized and highly populated area of Thailand, it provides a contrasting environment to the other two provinces.

Evaluation of object recognition

We use two metrics to evaluate container detection: (1) detection of containers, grouping all eight types together, and (2) detection along with categorization into one of the eight types. For the measurement of object recognition accuracy, we use the standard approach of determining the agreement between each detection bounding box with ground truth boxes in an image by calculating area of intersection over union (IoU). An IoU value of 0.5 or greater is considered to be a true positive [44]. An undetected object is counted as a false negative and a falsely detected object is counted as a false positive. Table 1 shows the performance on the test set which was a randomly selected 10% of the entire dataset. The results for container detection are shown in the last column: precision is 0.90, recall is 0.92, and the F-score is 0.91. Results for the detection along with classification are shown in the remaining columns. The highest F-scores are achieved for potted plant (0.91) and old tire (0.92). The bin category has a high precision but low recall because bins and buckets are very similar in shape so that some bins are wrongly tagged as buckets; this also lowers the precision of the bucket category.

Table 1. Object recognition accuracy at 0.5 recognition confidence threshold for each category of container and grouping all container types. The average precision is calculated from the precision/recall curve as the average overall recall levels.

	Bin	Ceramic Bowl	Bucket	Large Jar	Misc short open	Potted Plant	Old Tire	Misc long open	All container types
Precision	1.00	0.78	0.83	0.94	0.76	0.89	0.92	0.79	0.90
Recall	0.23	0.89	0.94	0.82	0.91	0.94	0.93	0.86	0.92
F-score	0.37	0.83	0.88	0.88	0.83	0.91	0.92	0.82	0.91
Average Precision	0.42	0.51	0.86	0.71	0.46	0.75	0.81	0.63	-

Analysis of Container Counts

Our software was used to retrieve GSV images from Bangkok (790,450 images), Nakhon Si Thammarat (958,027 images) and Krabi provinces (386,819 images) at every 50 meters and to detect all containers in those images. Details are shown in Tables A.1 - A.3 in the Appendix. Image coverage of the three provinces varied considerably. Bangkok had the best image coverage at a mean of 77.06% of total area over all districts, followed by Nakhon Si Thammarat at 8.40%, and Krabi at 7.31%. Due to the limited availability of accurate shapefiles for Bangkok, we were not able to gather GSV images for Phra Khanong district and for nine sub-districts in other districts. These were left out of the calculations of density values so as not to bias the values down. Image coverage also varied considerably over the districts of each province. Bangkok had 100% image coverage for 21 out of 49 districts and a low of 15.45% for one district. In Nakhon Si Thammarat the coverage ranged from 19.7% to 2.4% and in Krabi from 11.36% to 5.15%. A total of 298,391 containers were identified in Bangkok, 84,609 in Nakhon Si Thammarat, and 30,025 in Krabi. Container density also varied considerably. Bangkok had the highest container density (containers/km^2 image area) over districts (Mean = 358.90, Standard variation (SD) = 119.79), followed by Nakhon Si Thammarat (Mean = 98.71, SD = 32.56), and then Krabi (Mean = 84.76, SD = 24.87). The highest container density of 729.75 was found in Din Daeng district of Bangkok. Container density per population was markedly more uniform across the three provinces but showed considerable variation among districts within the provinces. Krabi had the highest density by population (Mean = 7.12, SD = 2.90), followed by Bangkok (Mean = 5.30, SD = 3.19) and Nakhon Si Thammarat (Mean = 5.20, SD = 1.64). The highest density by population was found in Khanna Yao district of Bangkok at 17.71 containers per 100 population. As would be expected, the number of containers is well correlated with population in Nakhon Si Thammarat ($r(23)=0.804$, $p < 0.001$) and moderately in Bangkok ($r(49) = 0.654$, $p < 0.001$). For Krabi there are too few districts to compute a meaningful correlation.

Among the eight detected categories of containers, potted plants and buckets account for the vast majority in all three provinces. In the highly urbanized area of Bangkok, potted plants account for 51.84% of containers and buckets for 29.96%. In the more rural provinces, the proportion is reversed. In Nakhon Si Thammarat, buckets and potted plants account for 45.14% and 32.08%, respectively and in Krabi they account for 52.27% and 27.56%, respectively. Figure 7 shows the variation of relative proportions of container types over all sub-districts of the three provinces. Bangkok had the least variation in prevalence of container types while Nakhon Si Thammarat had the highest. For example, in Sichon district of Nakhon Si Thammarat, bins accounted for 23.03% of all detected containers, and in Tham Phannara districts, old tiers accounted for 21.48%.

To validate the container counts from GSV images, we compared them with counts from manual surveys. Chumsri et al. [45] conducted a study in five sub-districts of Lansaka district of Nakhon Si Thammarat in which they gathered indoor and outdoor container counts and larval counts in the wet and dry seasons of 2015. Our GSV images were taken during the dry season of 2016, so we compare our counts to their outdoor dry season counts. Since the absolute container counts from the two studies are not comparable due to different sampling techniques, we compare the relative counts over the five sub-districts in each study by normalizing by the highest count in each study. The result is shown in Figure 8. The relative counts over four of the sub-districts have strong agreement but the counts disagree for Khao Kaeo sub-district. Table A.5 shows the analysis of our container counts from GSV images over the five sub-districts. Our analysis shows that Khao Kaeo has the lowest coverage of GSV images at only 1.39% and a container count of 24, compared to Khun Thale: 11.71% with 446 containers, Thadi: 7.20% with 445 containers, Lansaka: 3.39% with 246 containers, and Kamlon: 2.82% with 318 containers. The low GSV image coverage would account for the relatively low container count from GSV images.

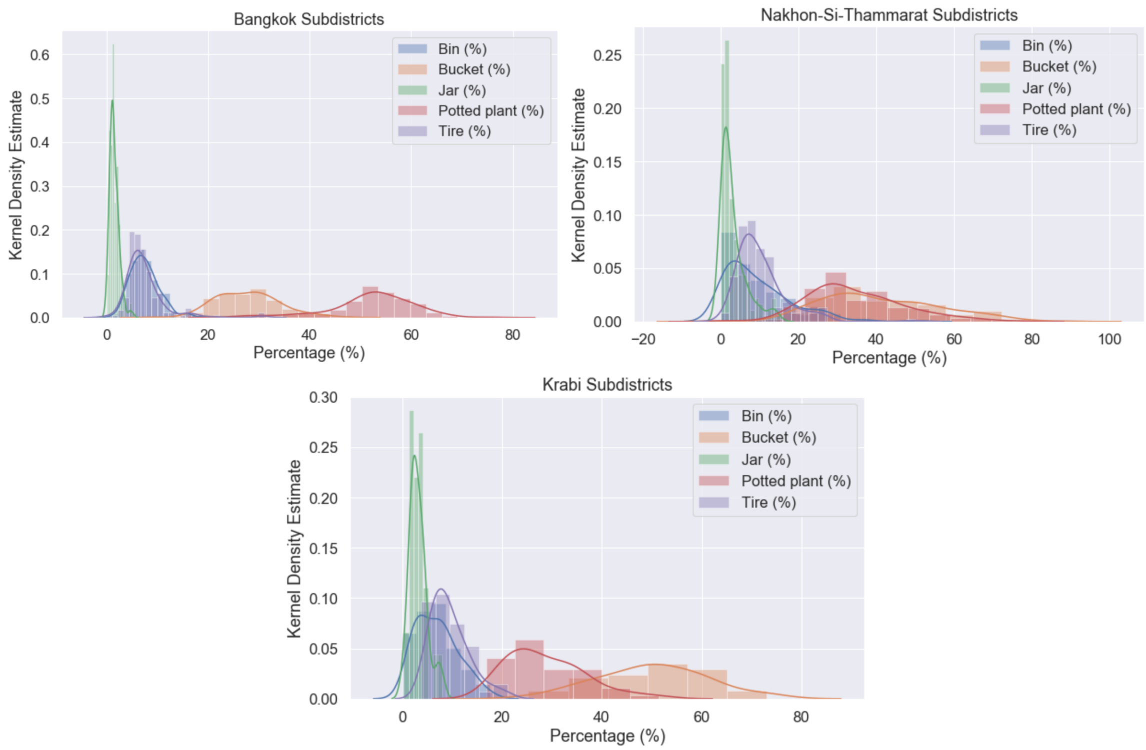


Figure 7. Distribution of relative prevalence of five most common container types (bin, bucket, jar, potted plant, tire) over sub-districts of Bangkok, Nakhon Si Thammarat and Krabi provinces. Kernel density estimation was applied to smooth the values.

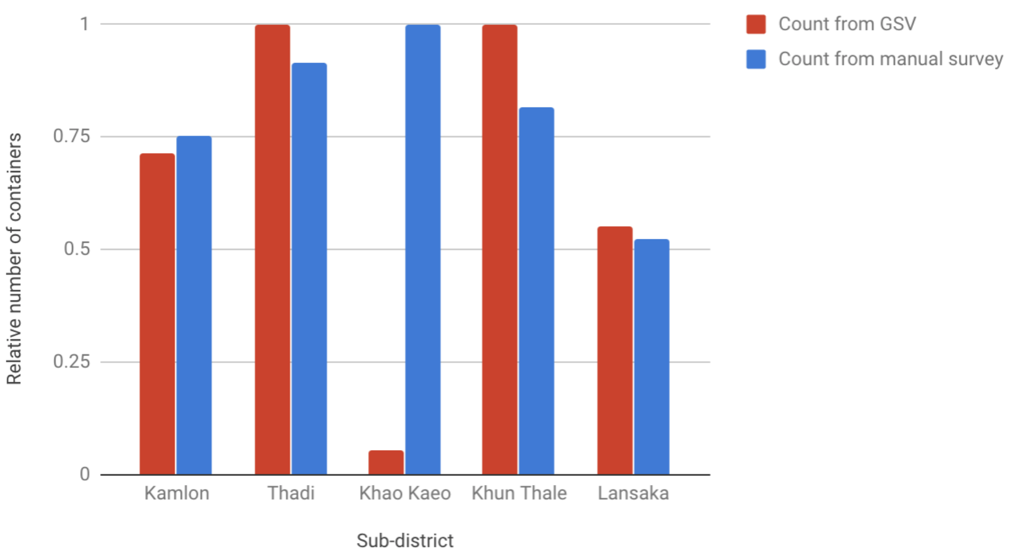


Figure 8. The relative numbers of containers in Lansaka District, Nakhon Si Thammarat from analysis of GSV images and from manual surveys [45]. Values are shown relative to the highest count over the sub-districts for each study.

Comparison with larval survey data

Container counts are useful to the extent that they are indicative of potential for vector abundance. We evaluated this by comparing container density values (containers/km^2 land area) derived from GSV images with data from manual larval surveys. We carried out this comparison for the province of Nakhon Si Thammarat, which was chosen because, among provinces in Thailand, it has the highest number of manual surveys in recent years and is consistently one of provinces with the highest incidence of dengue cases. Container density values were generated by retrieving 958,027 GSV images from Nakhon Si Thammarat province and running them through the convolutional neural net for object recognition. Analysis of the metadata showed that the vast majority of images were taken in 2016.

We obtained seven years (2011 - 2017) of village-level larval survey data for Nakhon Si Thammarat from the Ministry of Public Health of Thailand. The larvae were manually identified by the village health volunteers who walked door-to-door and checked whether the larvae were present in containers within or around the houses surveyed. The data from each survey was reported using three indices: Container Index (percentage of water-holding containers infested with larvae or pupae), House Index (percentage of houses infested with larvae and/or pupae), and Breteau Index (number of positive containers per 100 houses inspected). We use the Breteau Index (BI) for comparison since it is conceptually closest among these to our measure of container density and is considered the most useful of the three indices in estimating the *Aedes* density at a location [46].

To be meaningful, comparison of container density values and BI values should be done with data collected at roughly the same time. To maximize the amount of manual survey data, we used BI data from a 3-year time window: 2015 - 2017. This is justified by the fact that while the location or presence of individual containers changes over time, the total number (absent major intervention efforts) is quite stable. We excluded outliers from container density counts and BI values by using a cutoff of $\mu \pm \sigma$, which left a total of 53 sub-districts for which we had container density counts and average BI values. The first row of Table 2 shows the number of containers of each type over the 53 sub-districts. Detailed statistics are provided in Table A.4 in the Appendix.

Table 2. Description of detected containers used in comparison with larval surveys for entire year, dengue season and non-dengue season.

	N Sub-district	Bin	Ceramic Bowl	Bucket	Big Jar	Potted Plant	Old Tire	Misc short open container	Misc tall open container	Total
Entire Year	53	2,605	129	11,621	563	7,379	2,552	174	22	25,045
Dengue Season	29	1,522	85	7,192	328	4,201	1,529	119	11	14,987
Non Dengue Season	45	2,038	105	9,447	500	6,209	2,181	141	19	20,640

Table 3. Description of Breteau Index data used in analyses: number of surveys per sub-district (N), mean value of BI, and SD. District numbers shaded green are those 29 used in dengue season analysis.

	District	Sub-district	N	Mean	SD		District	Sub-district	N	Mean	SD		District	Sub-district	N	Mean	SD
1	Mueang	Tha Rai	1	68.0		19	Cha-uat	Tha Pracha	5	31.2	7.9	37	Thung Yai	Kurae	24	17.2	3.7
2	Mueang	Kamphaeng Sao	1	57.5		20	Cha-uat	Wang Ang	17	23.0	6.2	38	Thung Yai	Krung Yan	59	13.2	2.6
3	Mueang	Chai Montri	1	53.3		21	Cha-uat	Ban Tun	10	30.2	3.6	39	Sichon	Thung Prang	2	35.5	13.4
4	Mueang	Mamuang Song Ton	1	57.5		22	Cha-uat	Khon Hat	1	37.5		40	Sichon	Sao Phao	1	50.0	
5	Phrom Khiri	Phrom Lok	1	30.0		23	Cha-uat	Ko Khan	7	17.9	6.2	41	Hua Sai	Na Saton	2	72.0	90.5
6	Phrom Khiri	In Khiri	2	50.0	3.5	24	Cha-uat	Khuan Nong Hong	16	29.5	6.6	42	Bang Khan	Bang Khan	34	6.2	1.5
7	Phrom Khiri	Thon Hong	2	33.5	2.1	25	Cha-uat	Khao Phra Thong	11	31.8	4.6	43	Bang Khan	Ban Lamnao	23	6.3	1.3
8	Lan Saka	Tha Di	1	30.0		26	Cha-uat	Nang Long	1	40.0		44	Bang Khan	Wang Hin	3	7.5	0.0
9	Lan Saka	Kamlon	2	33.5	0.7	27	Tha Sala	Sa Kaeo	2	15.0	8.5	45	Bang Khan	Ban Nikhom	13	5.6	1.1
10	Lan Saka	Khun Thale	2	70.0	53.0	28	Tha Sala	Thai Buri	1	33.3		46	Tham Phannara	Tham Phannara	2	27.0	0.0
11	Chawang	Na Wae	11	15.7	2.8	29	Thung Song	Nong Hong	1	22.5		47	Chulabhorn	Thung Pho	10	33.1	5.3
12	Chawang	Huai Prik	6	16.2	1.0	30	Thung Song	Khao Ro	3	54.5	16.1	48	Chulabhorn	Na Mo Bun	1	32.5	
13	Chawang	Na Khliang	2	15.0	3.5	31	Thung Song	Thi Wang	4	41.2	9.2	49	Phra Phrom	Na Phru	2	9.5	4.9
14	Phipun	Kathun	8	19.0	2.0	32	Thung Song	Namtok	3	25.8	2.9	50	Phra Phrom	Na San	1	42.5	
15	Phipun	Khao Phra	2	22.1	1.2	33	Thung Song	Na Pho	5	43.0	9.4	51	Nopphitam	Nopphitam	3	38.3	18.8
16	Chian Yai	Thong Lamchiak	1	15.0		34	Na Bon	Na Bon	1	22.5		52	Nopphitam	Krung Ching	1	10.0	
17	Chian Yai	Karaket	1	32.5		35	Na Bon	Kaeo Saen	3	62.8	29.0	53	Chaloem Phra Kiet	Thang Phun	2	10.0	0.0
18	Cha-uat	Cha-Uat	1	42.5		36	Thung Yai	Thung Sang	1	12.5			Average Survey		6.06		

A complicating factor in our analysis is that the larval surveys were carried out at the village level. Producing corresponding container density counts would require reliable village shapefiles, which are not available in Thailand. Since shapefiles are available for sub-districts, we carried out the comparative analysis at the sub-district level. As shown in Table 3, the BI for each sub-district was approximated by taking the average of the BI values of all villages in that sub-district.

An initial straightforward approach to evaluating the agreement between container density and BI is to compute an overall container density by summing the numbers of containers of the eight different types. Computing the correlation between this and BI over 53 sub-districts for the entire year yields a Pearson correlation of 0.3416 ($p = 0.0123$) as shown in Figure 9A. This weak correlation is not surprising since we are measuring the relation between container density and BI during some months when there is little or no rain; thus few larvae in the counted containers. We would expect the correlation to naturally be low during the dry season and higher during the rainy season. To test this we separately measured the correlation with BI values collected during the wet dengue season, which in Nakhon Si Thammarat is June - November [47], and the remaining months, the non-dengue season. For the dengue season, this left 29 sub-districts with BI data and for the non-dengue season this left 45 sub-districts. Rows two and three in Table 2 show the numbers of containers of each type for the dengue and non-dengue seasons, respectively. Over the dengue season, the Pearson correlation is moderately strong 0.5242 ($p = 0.0035$), as shown in Figure 9B, while over the non-dengue season the Pearson correlation is a weak 0.1631 ($p = 0.2844$), as shown in Figure 9C.

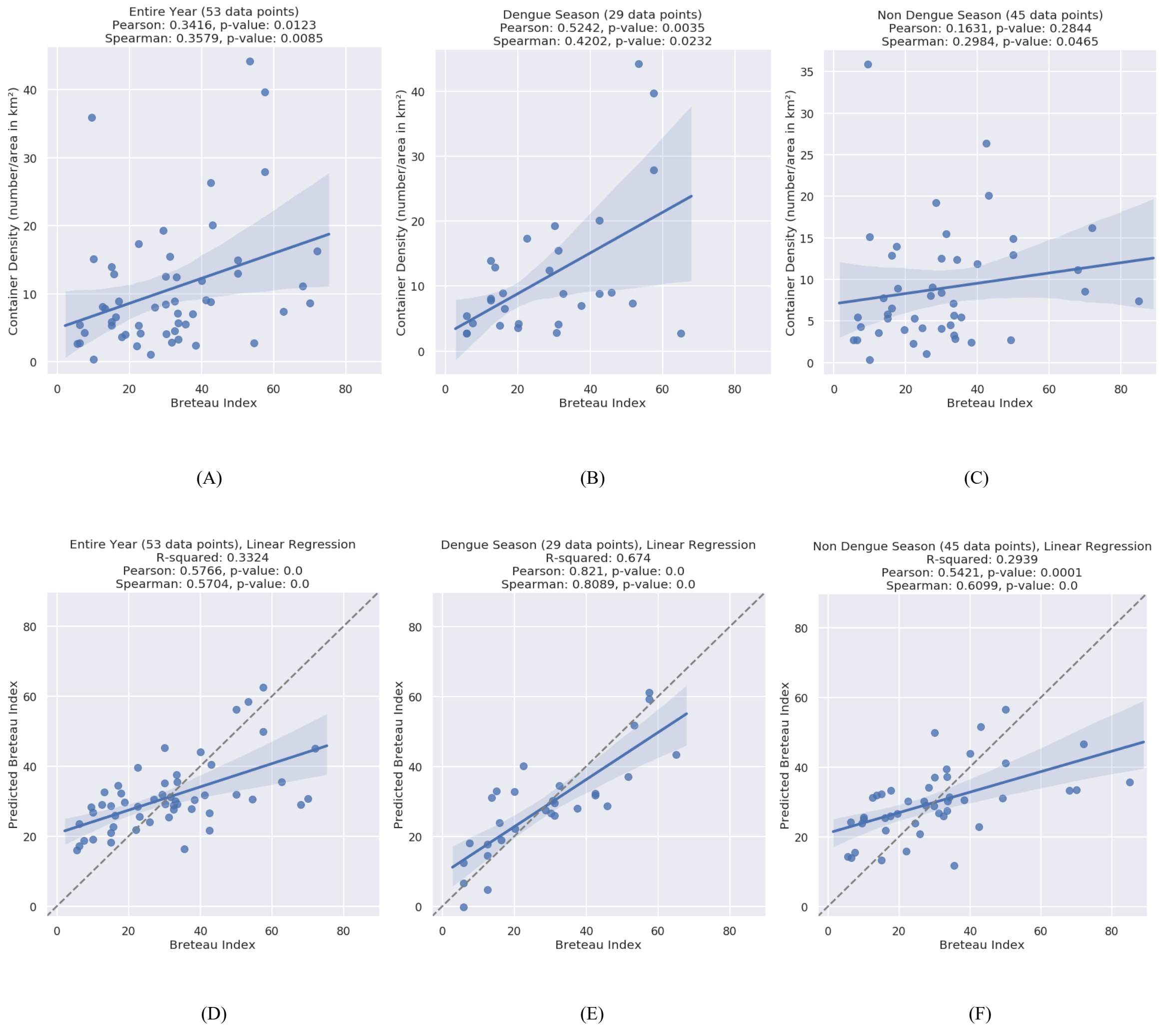


Figure 9. Correlation between container density by land area and BI for (A) entire year, (B) dengue season, and (C) non-dengue season, and predicted vs actual values of BI for multivariate linear regression model for (D) entire year, and (E) dengue season, and (F) non-dengue season. The solid line is a linear trendline which is an indication of the linear (Pearson) correlation between the two variables.

Vector abundance in a given area depends on container density as well as container productivity, with productivity often varying greatly among container types [48] [49] [45]. Thus, a more precise relation between container counts and BI can potentially be obtained by analyzing the relationship using the disaggregated counts of the various container types. We created multiple linear regression models with container densities for the eight types of containers as the independent variables and BI as the dependent variable. Evaluation of the fitted linear model shows a moderately strong Pearson correlation with the BI values of 0.5766 ($p < 0.0001$) for entire year, 0.5421 ($p = 0.0001$) for the non-dengue season, and a significantly high Pearson correlation of 0.8210 ($p < 0.0001$) for the dengue season, as shown in Figures 9D, 9E, and 9F, respectively. The standardized beta coefficients for the dengue season model, shown in Table 4, indicate that potted plants and large jars are the most important types of containers in predicting BI values within the 29 sub-districts. Interestingly, these are not the most prevalent types of containers in the sub-districts. The most prevalent are buckets (47.46%), potted plants (28.42%), and tires (10.53%). Large jars represent only 2.31% of the detected breeding sites. This result conforms to results from previous entomological studies of the dengue vector in Thailand which found that potted plants and large jars are two of the most important breeding site types. The Ministry of Public Health [36] reports that among larval surveys carried out throughout the country, 70.82% of *Aedes aegypti* larvae are found in large jars. In a study of Aedes aegypti breeding sites in Kamphaeng Phet, Thailand, Koenradt et al. [32] found earthenware jars to be responsible for 33.1% of pupae production. A study of dengue vector breeding sites in Nakhon Si Thammarat found that the number of positive containers was higher in earthen containers (e.g., potted plants and large jars) than in plastic ones [50]. This analysis demonstrates the value of our data driven approach in identifying important container types, which is recognized as being essential in effective dengue control [51].

Table 4. Absolute standardized coefficients and p-values from linear regression for dengue season. The largest absolute values are the most important variables in the regression model.

	Absolute Standardized Coefficients							
	Potted Plant	Large Jar	Bin	Misc short open container	Old Tire	Bucket	Ceramic Bowl	Misc tall open container
Beta	**3.3577**	**2.0578**	0.6932	0.4863	0.3882	0.3501	0.2956	0.0435
p-value	0.0009	0.0002	0.0634	0.0142	0.1412	0.3119	0.2371	0.7925

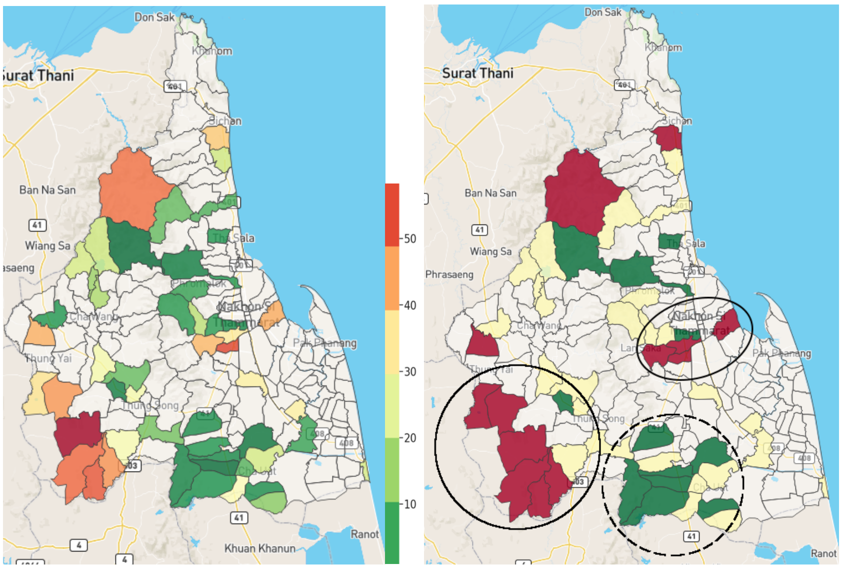
To understand conditions under which the linear regression models fit well and under which they do not, we carried out an analysis of the model residuals over the sub-districts using the symmetric mean absolute percentage error (SMAPE) which has the advantage of being independent of magnitude of the values being estimated. This was applied to the single value for each sub-district so that the value of n is just 1 and the formula becomes (|F - A|) / (|F| + |A|), where A is actual value and F is the predicted value; thus for clarity we use the term symmetric absolute percentage error (SAPE). Figures 10 A.1 and A.2 show the SAPE values for the entire year using a gradient color scheme and thresholding, respectively. Figures 10 B.1 and B.2 similarly show the SAPE values for only the dengue season using gradient color scheme and thresholding. Since the results are quite similar, we will restrict our discussion to the entire year, using the thresholded colormap which most clearly displays the areas where the models are accurate or inaccurate. The map uses 25% and 75% quantile threshold values to categorize sub-districts into three classes: good fit (dark green), average fit (yellow), and poor fit (dark red). In the figure we can observe some amount of clustering of regions of good fit and poor fit.

The solid circle delineates a cluster of six sub-districts where the model fit is poor. Four of the sub-districts are in Bang Khan district and the other two are in Thung Yai district, which are mountainous areas. A previous study by Preechaporn et al. [33] examining the effect of topography on key breeding sites in Nakhon Si Thammarat found that in these mountainous areas the key containers for *Aedes aegypti* were preserved areca jars and for *Aedes albopictus* were metal boxes. These two container types are not detected by our object recognition software.

The oval delineates another cluster of four sub-districts where model fit is poor. These sub-districts (Tha Rai, Mueang district; Khun Thale, Lan Saka district; Na Phru and Na San, Phra Phrom district) are urban areas with high population density. A plausible explanation is that in such urban areas, indoor containers represent a large proportion of breeding sites which cannot be detected in the GSV images. In urban environments, *Aedes aegypti* is more prominent than *Aedes albopictus* and the former prefer indoor breeding sites [52] [53]. In a study of the effect of urbanization on the presence of *Aedes aegypti* and *Aedes albopictus* in Chiang Mai, Thailand, Tsuda et al. [54] found a larger number of mosquito larvae indoors than outdoors in their urban study area and the reverse in their rural study area.

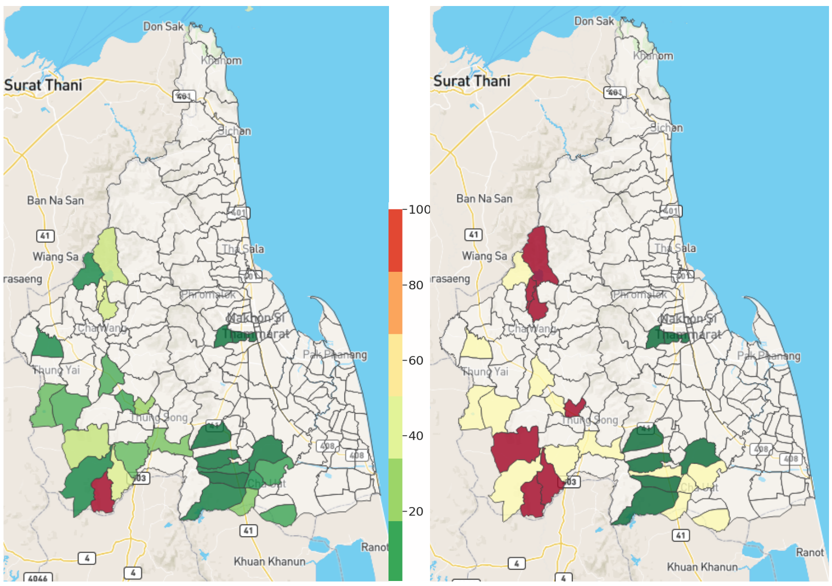
The dashed circle in the figure delineates a cluster of sub-districts, mostly in Cha-Uat district, where the model fit is good. A previous study of the ecology of *Aedes* mosquitos in Kreang sub-district of Cha-Uat district [55] found plastic buckets to be the most common breeding sites. Our analyses show plastic buckets to be the most prevalent containers in Cha-Uat district (51.73%) as shown in Table A.2.

(A) Map displaying residuals for sub-districts for entire year



(A.1) (A.2)

(B) Map displaying residuals for sub-districts for Dengue Season



(B.1) (B.2)

Figure 10. Choropleth maps of SAPE values for the multivariate linear models for (A) entire year, and (B) dengue season. Where (1) is the gradient colormap of SMAPE values, and (2) is the thresholded colormap using the 25% and 75% quantiles as threshold values. Map data © Mapbox, © OpenStreetMap

Figure 11 shows a scatter plot of the SAPE of the model predictions for the sub-districts versus the BI values. The same thresholded color coding is used as in the map in Figure 10A.2. The values follow a polynomial distribution. Many of the high errors occur for low values of BI, which correspond to very low absolute errors. Accuracy tends to be good toward the middle range of BI values. It then becomes worse for the higher BI values. Two of these points, shown in red, correspond to two of the districts with high population density discussed above.

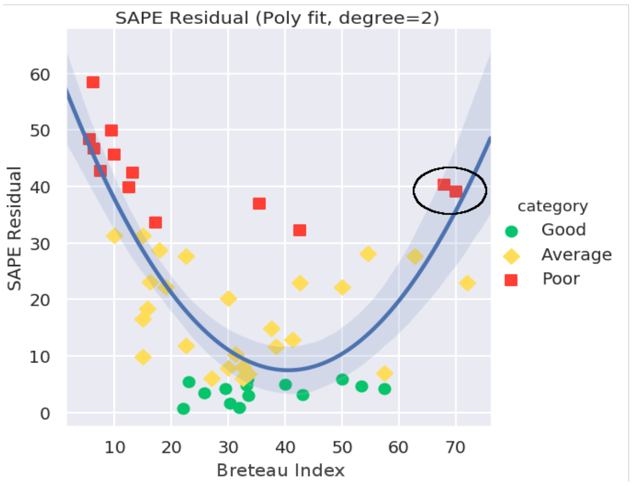


Figure 11. Scatter plot of SAPE residual values of sub-district predictions versus Breteau index

Comparison with dengue cases

To evaluate the value of the container counts obtained from GSV images for dengue risk mapping, we compared the container density counts with dengue incidence in the three provinces. Dengue case data was obtained from the Ministry of Public Health of Thailand [56]. The number of dengue cases was initially recorded at local hospitals with Form 506 and accumulated at the Bureau of Epidemiology (BoE) for further collation and analysis [57]. A dengue case is defined according to the definitions established by the BoE [58]. The cases are classified into three levels: suspected, probable and confirmed. While only confirmed cases are mandatorily reported, Report 506 also includes suspected and probable cases. We made use of all cases identified and reported by the local health officers. The dengue incidence rate over time for the three provinces is shown in Figure 12. For the analysis we used the average incidence rate (cases/10,000 population) in each sub-district of Nakhon Si Thammarat, Krabi, and Bangkok over the same 3-year period 2015 - 2017 as for the BI data. The average was taken in order to smooth the data. Table 5 provides descriptive statistics for these average values.

Table 5. Description of time-averaged dengue incidence rate over the period of analysis (2015-2017).

Province (# of sub-districts included in this study)	Dengue cases per 10,000 population (in a sub-district) (2015-2017 average)					
	Min	Q1	Median	Mean	Q3	Max
Nakhon Si Thammarat (167)	7.142	31.455	44.545	46.222	60.084	112.281
Krabi (47)	9.298	23.223	39.344	56.163	70.141	202.802
Bangkok (159)	20.81	56.93	70.73	76.04	89.11	244.97

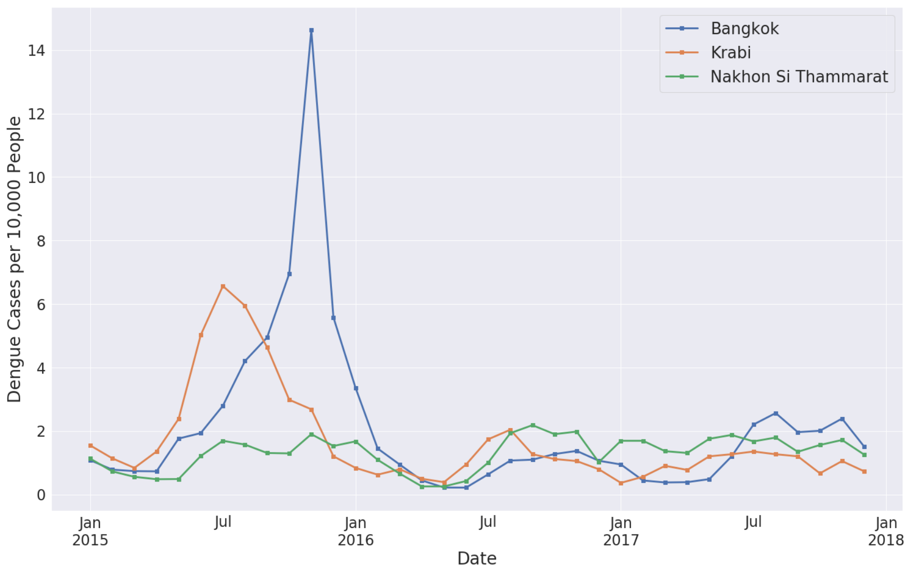
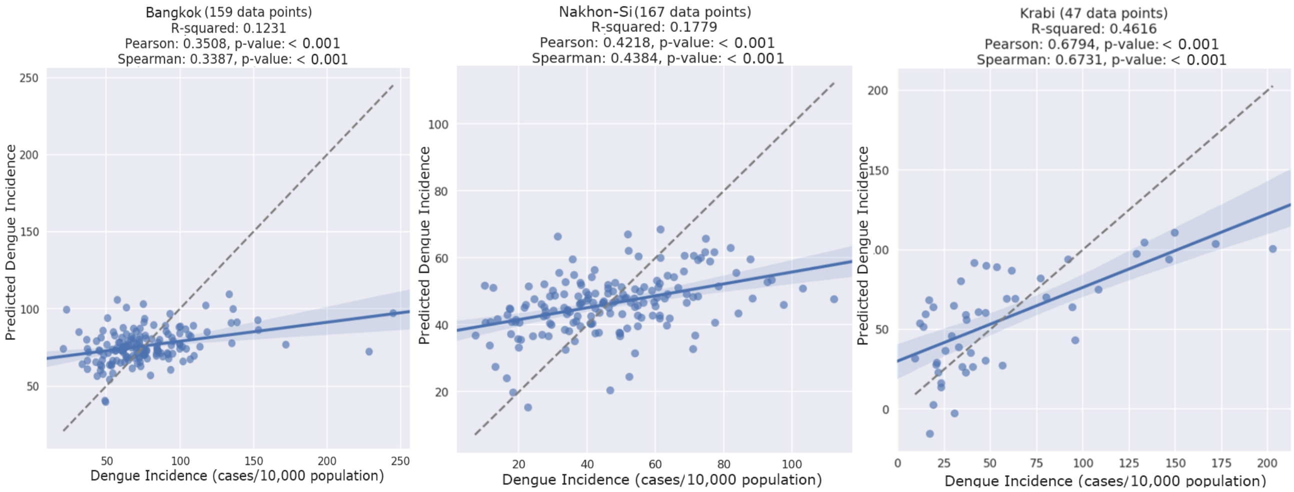


Figure 12. Time series of dengue incidence rate for Bangkok, Krabi, and Nakhon Si Thammarat provinces.

A multivariate linear regression was performed over all sub-districts in each province, using container density as a function of population (containers/100 population) for each container type as independent variables and dengue incidence rate as the dependent variable. As shown in Figure 13, the model was weakly predictive for Bangkok (R-squared = 0.123, $p < 0.001$) and for Nakhon Si

Thammarat (R-squared = 0.1779, $p < 0.001$) and moderately predictive for Krabi (R-squared = 0.4616, $p < 0.001$).



(A) (B) (C)

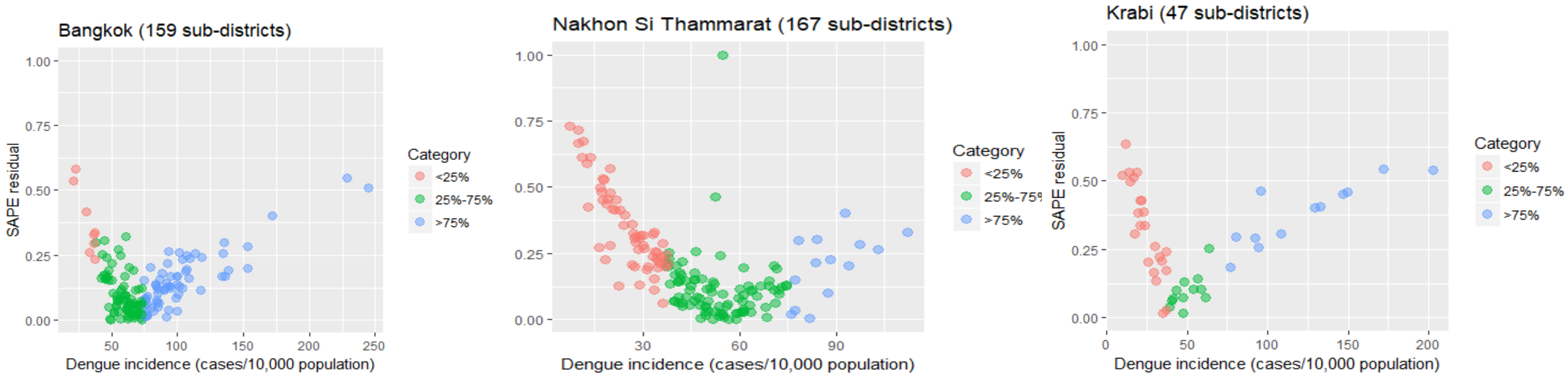
Figure 13. Scatter plots of predicted vs actual values of dengue incidence for multivariate linear regression models for (A) Bangkok, (B) Nakhon Si Thammarat, and (C) Krabi for the period 2015 - 2017.

Table 6 shows the standardized coefficients for the eight container types for each province. For Bangkok the most important containers are potted plants and large jars; for Krabi they are potted plants and misc short open containers; and for Nakhon Si Thammarat they are large jars and potted plants. The result for Nakhon Si Thammarat is similar to the results of the linear regression with BI, which showed the most important containers to be potted plants and large jars (Table 4).

Table 6. Absolute standardized coefficients and p-values from Linear regression in predicting dengue cases in each province e.g., the features with the most beta are the important variables in the regression model.

	Absolute Standardized Coefficients - Bangkok							
	Potted Plant	Large Jar	Ceramic Bowl	Bucket	Bin	Misc tall open container	Old Tire	Misc short open container
Beta	0.4734	0.3804	0.1857	0.1439	0.0997	0.0462	0.0457	0.0342
p-value	0.0036	0.0059	0.1253	0.4649	0.4779	0.6347	0.6529	0.7631
	Absolute Standardized Coefficients - Nakhon Si Thammarat							
	Large Jar	Potted Plant	Misc tall open container	Ceramic Bowl	Old Tire	Bucket	Bin	Misc short open container
Beta	0.4233	0.3377	0.2131	0.1150	0.0807	0.0692	0.0394	0.0312
p-value	0.0000	0.0029	0.0243	0.2384	0.3836	0.4655	0.6644	0.7741
	Absolute Standardized Coefficients - Krabi							
	Potted Plant	Ceramic Bowl	Bucket	Old Tire	Misc tall open container	Misc short open container	Large Jar	Bin
Beta	0.7199	0.4892	0.3321	0.3158	0.2800	0.2381	0.1211	0.0556
p-value	0.0768	0.0298	0.1257	0.1243	0.0898	0.1808	0.5791	0.7457

Figure 14 shows scatterplots of the model residuals versus dengue incidence rate for the three provinces. The plots show that the linear models predict dengue incidence best in the mid range of incidence. The high SAPE residuals for low values of dengue incidence represent only small absolute errors. The high SAPE residuals for high values of dengue incidence represent the fact that container counts provide a measure of the degree to which the environment can support proliferation of the vector but are not in and of themselves predictive of dengue outbreaks.



(A) (B) (C)

Figure 14. Scatterplots of SAPE residual values of district predictions versus dengue incidence for (A) Bangkok, (B) Nakhon Si Thammarat, (C) Krabi. Points are colored using the 25% and 75% quantiles as threshold values.

Conclusions

We presented a pipeline to detect and map containers using images from Google Street View. The central component in this pipeline is the Faster R-CNN object recognition network from which we used five existing object categories from the COCO dataset and used transfer learning to train an additional three. Evaluation on a test set of images yielded an F-score accuracy of 0.91 for the problem of detecting any of eight types of containers. While the eight object categories in the network cover a number of the most important container types for the dengue vector in Thailand, there are some notable missing types. Cement tanks are known to be important breeding sites throughout Thailand [34] [35] . These were not included in the network because they are not in the COCO dataset and images to use for transfer learning are not readily available. In addition, numerous other container types are important breeding sites regionally. For example, one study in Nakhon Si Thammarat [33] found *Aedes aegypti* larvae mostly in preserved areca jars in mangrove and mountainous areas, and *Aedes albopictus* larvae mostly in preserved areca jars in mangrove areas and in metal boxes in mountainous areas. Such container types could also be added to produce a more comprehensive catalog of containers. Finally, very small containers such as cans and bottles are difficult to recognize in GSV images. This could be partially addressed by using scene recognition techniques [25] to detect areas such as garbage dumps that have high concentrations of such containers.

Despite these limitations of container coverage, a simple multi-linear regression model relating densities of the eight container types with Breteau Index values for 29 sub-districts in Nakhon Si Thammarat province of Thailand yields an R-squared value of 0.674 during the dengue season. While this result is highly encouraging, the study area is yet small. A larger study over a diversity of types of geographic regions would help to further validate these results. A similar multi-linear regression model relating container densities to dengue incidence at the sub-district level in Bangkok, Nakhon Si Thammarat, and Krabi yields less strong results. The best predictive accuracy is attained for Krabi, with an R-squared of 0.462. This weaker result is not surprising since numerous other factors influence the incidence of dengue such as rainfall, temperature, and population demographics. In ongoing work, we are constructing predictive models of dengue using these factors and the container densities in order to understand and quantify the added value of the container density data in dengue prediction. We expect that container densities will help to account for spatial variation in dengue incidence, which is an aspect that is not yet well addressed in the work on dengue predictive models. Incorporation of container densities in the models will also permit evaluation of alternative control strategies since dengue control consists largely of elimination of breeding sites.

While GSV data is an excellent data source for evaluating the potential usefulness of the approach presented in this study, it has a number of limitations that make it less ideal for supporting practical control efforts. These limitations concern mostly temporal and spatial data coverage. As mentioned earlier, GSV data is updated only at infrequent intervals. While we expect container densities to not vary much over time for large areas, targeting control efforts requires high spatial resolution of risk maps and predictive models. Thus the lack of recent updates becomes more of an issue as we move to higher spatial resolution. In terms of the spatial coverage, GSV images cover only areas along roads and so do not cover areas such as empty lots and back yards. These limitations can be addressed through the use of existing tools for gathering geotagged images. These include smartphone applications like Mapillary (www.mapillary.com) or Open Street Cam (openstreetcam.org) for producing street view types of images and drones to gather high-resolution images. We plan on experimenting with these data sources.

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Appendix

Table A.1 Areas, image coverage, population, containers data in district level in Bangkok, Thailand

District Name	Area (km^2)	Area of GSV images (km^2)	GSV image coverage (%)	Population	Number of containers	Containers per km^2 land	Containers per km^2 image area	Containers per 100 persons	Relative proportions of container types (%)							
									Jar	Bucket	Potted plant	Tire	Bin	Bowl	Misc short open	Misc long open
Phra Nakhon	5.53	5.53	100.00	52,522	2,527	456.96	456.96	4.81	0.87	20.14	61.06	4.00	6.61	3.44	2.89	0.99
Dusit	11.69	5.86	50.13	98,450	1,158	99.06	197.61	1.18	0.86	25.22	54.40	6.65	8.98	2.07	1.73	0.09
Nong Chok	248.15	38.33	15.45	167,844	7,432	29.95	193.90	4.43	2.27	36.05	40.76	9.08	10.71	0.63	0.40	0.09
Bang Rak	4.14	4.14	100.00	47,308	1,956	472.46	472.46	4.13	0.82	24.23	54.70	7.31	6.44	3.48	2.30	0.72
Bang Khen	42.28	39.62	93.71	190,828	14,879	351.92	375.54	7.80	1.76	29.18	51.51	5.56	10.36	0.87	0.57	0.19
Bang Kapi	28.47	28.47	100.00	148,392	14,832	520.97	520.97	10.00	1.21	29.79	54.15	5.05	7.69	1.05	0.84	0.21
Pathum Wan	8.29	8.29	100.00	49,594	2,118	255.49	255.49	4.27	0.85	21.44	56.19	9.87	6.09	2.55	2.27	0.76
Pom Prap Sattruphai	2.58	2.58	100.00	47,450	1,637	634.50	634.50	3.45	0.73	22.97	55.96	10.75	3.67	2.81	2.81	0.31
Min Buri	63.07	27.75	44.00	141,214	9,736	154.37	350.85	6.89	2.32	34.81	46.57	6.70	8.19	0.72	0.58	0.12
Lat Krabang	132.70	40.63	30.62	171,933	5,617	42.33	138.25	3.27	2.62	41.32	34.02	14.69	5.70	0.69	0.84	0.12
Yannawa	12.90	11.54	89.46	79,574	2,700	209.30	233.97	3.39	1.26	26.78	52.11	7.89	9.04	1.67	1.04	0.22
Samphanthawong	1.44	1.44	100.00	24,785	683	474.31	474.31	2.76	0.44	23.87	52.42	7.17	8.49	3.66	2.93	1.02
Phaya Thai	9.51	9.51	100.00	72,102	2,904	305.36	305.36	4.03	0.79	21.38	57.58	7.33	9.30	1.72	1.31	0.59
Thon Buri	8.73	8.73	100.00	111,027	3,018	345.70	345.70	2.72	1.52	27.87	54.74	6.46	4.71	2.75	1.62	0.33
Bangkok Yai	6.50	4.19	64.46	67,887	1,249	192.15	298.09	1.84	1.76	21.78	63.89	4.32	4.72	1.84	1.04	0.64
Huai Khwang	16.84	16.84	100.00	81,190	7,147	424.41	424.41	8.80	1.12	25.44	54.36	7.68	9.21	1.01	0.87	0.32
Khlong San	6.16	5.36	87.01	73,871	1,881	305.36	350.93	2.55	1.91	27.11	54.44	6.91	5.53	2.82	1.12	0.16
Taling Chan	36.92	20.80	56.34	105,289	3,473	94.07	166.97	3.30	1.44	28.07	53.21	8.41	7.08	0.92	0.75	0.12
Bangkok Noi	12.72	11.33	89.07	112,581	3,819	300.24	337.07	3.39	1.28	24.51	58.68	5.92	7.54	0.86	1.00	0.21
Bang Khun Thian	126.04	30.72	24.37	179,768	7,264	57.63	236.46	4.04	1.98	35.35	44.34	7.90	8.40	0.98	0.81	0.23
Phasi Charoen	19.79	13.46	68.01	259,418	5,968	301.57	443.39	2.30	1.93	31.60	52.83	6.07	5.19	1.42	0.72	0.23
Nong Khaem	37.35	22.42	60.03	155,229	8,745	234.14	390.05	5.63	3.18	31.23	51.39	6.21	6.38	0.88	0.59	0.14
Rat Burana	12.72	8.74	68.71	83,248	2,862	225.00	327.46	3.44	1.82	31.62	49.58	6.81	8.00	1.05	0.87	0.24
Bang Phlat	12.18	12.18	100.00	93,771	3,356	275.43	275.43	3.58	2.09	24.52	57.24	6.62	6.91	1.19	1.22	0.21
Din Daeng	8.74	8.74	100.00	123,966	6,378	729.75	729.75	5.14	1.22	29.18	49.80	5.97	10.44	1.96	1.11	0.31
Bung Kum	24.16	24.16	100.00	285,225	10,934	452.57	452.57	3.83	1.60	30.34	54.35	5.51	6.68	0.95	0.42	0.15
Sa Thon	7.49	7.49	100.00	80,497	3,145	419.89	419.89	3.91	1.02	22.48	59.46	7.50	5.98	1.97	1.21	0.38
Bang Su	13.30	9.34	70.23	126,136	2,935	220.68	314.28	2.33	1.26	29.37	52.98	5.83	8.89	0.99	0.55	0.14
Chatuchak	33.71	33.71	100.00	158,130	12,732	377.69	377.69	8.05	1.40	25.79	55.59	7.29	7.46	1.33	0.95	0.20
Bang Kho Laem	8.58	6.89	80.30	90,377	2,847	331.99	413.07	3.15	0.84	25.50	53.95	7.20	9.45	1.62	1.12	0.32
Prawet	55.42	31.97	57.69	294,501	6,967	125.70	217.93	2.37	2.01	31.62	47.06	6.42	11.31	0.79	0.66	0.13
Khlong Toei	13.66	11.53	84.41	188,739	3,018	220.94	261.65	1.60	1.03	20.74	57.42	6.63	10.11	1.42	2.12	0.53
Suan Luang	24.88	24.88	100.00	121,740	8,607	345.94	345.94	7.06	1.23	29.60	53.90	5.47	7.95	0.90	0.74	0.22
Chom Thong	23.90	16.26	68.03	208,214	8,126	339.97	499.65	3.90	1.26	32.21	53.45	5.69	5.33	1.00	0.90	0.18
Don Mueang	37.89	33.59	88.65	168,896	13,360	352.61	397.71	7.91	2.65	30.15	53.69	4.72	7.19	0.91	0.53	0.16
Rat Thewi	7.40	7.40	100.00	72,436	2,264	306.04	306.04	3.13	0.80	23.10	51.72	9.36	7.20	4.02	3.00	0.80
Lat Phrao	21.95	21.95	100.00	121,000	12,643	575.99	575.99	10.45	1.51	24.57	60.56	4.82	7.06	0.66	0.59	0.21
Wattana	13.41	13.41	100.00	84,528	4,271	318.49	318.49	5.05	0.87	24.21	54.17	5.94	10.87	1.86	1.42	0.66
Bang Khae	49.42	19.35	39.15	52,378	6,214	125.75	321.21	11.86	2.46	32.97	50.05	6.29	6.40	0.82	0.77	0.23
Lak Si	23.40	23.40	100.00	105,588	10,072	430.35	329.69	9.54	2.04	27.11	55.82	5.37	7.80	0.91	0.78	0.16
Sai Mai	45.03	25.30	56.18	200,374	10,717	238.00	423.54	5.35	3.44	30.61	49.44	5.57	9.50	0.76	0.50	0.18
Khanna Yao	26.19	26.19	100.00	49,575	8,780	335.19	333.74	17.71	1.66	30.72	51.99	5.25	9.00	0.71	0.51	0.16
Saphan Sung	28.96	22.86	78.94	94,982	7,990	275.90	349.52	8.41	2.25	26.90	60.32	5.09	4.35	0.59	0.36	0.15
Wang Thong Lang	17.62	17.62	100.00	112,849	8,948	507.80	507.80	7.93	1.30	32.80	46.67	7.15	10.27	1.02	0.61	0.18
Khlong Sam Wa	124.05	37.86	30.52	189,507	10,116	81.54	267.20	5.34	2.49	36.47	46.24	7.13	6.45	0.64	0.51	0.07
Bang Na	19.54	5.75	29.43	92,023	1,554	79.51	270.37	1.69	1.29	32.82	44.14	9.91	9.72	0.97	0.71	0.45
Thawi Watthana	53.40	25.33	47.43	77,890	4,207	78.79	166.10	5.40	2.21	30.45	44.69	11.31	10.27	0.40	0.52	0.14
Thung Khu	33.99	13.28	39.07	66,430	5,037	148.21	379.20	7.58	1.03	34.70	50.47	5.06	7.43	0.66	0.48	0.18

District Name	Area (km^2)	Area of GSV images (km^2)	GSV image coverage (%)	Population	Number of containers	Containers per km^2 land	Containers per km^2 image area	Containers per 100 persons	Relative proportions of container types (%)							
									Jar	Bucket	Potted plant	Tire	Bin	Bowl	Misc short open	Misc long open
Bang Bon	36.99	23.84	64.45	107,136	9,568	258.66	401.38	8.93	1.71	40.41	44.25	6.28	5.43	1.00	0.77	0.14
									Relative propotion over entire province (%):							
Summary	Total: 1,619.78	Total: 870.56	mean: 77.06 median: 88.65 SD: 26.14	Total: 5,888,392	Total: 298,391	mean: 294.70 median: 301.57 SD: 159.46	mean: 358.90 median: 345.94 SD: 119.79	mean: 5.30 median: 4.13 SD: 3.19	1.78	29.96	51.84	6.47	7.82	1.09	0.81	0.22

Table A.2 Areas, image coverage, population, containers data in district level in Nakhon Si Thammarat, Thailand

District Name	Area (km^2)	Area of GSV images (km^2)	GSV image coverage (%)	Population	Number of containers	Containers per km^2 land	Containers per km^2 image area	Containers per 100 population	Relative proportions of container types (%)							
									Jar	Bucket	Potted plant	Tire	Bin	Bowl	Misc short open	Misc long open
Mueang Nakhon Si Thammarat	564.61	111.50	19.70	271330	19915	35.27	178.62	7.34	1.78	41.91	36.77	6.30	11.77	0.57	0.81	0.10
Phrom Khiri	250.10	18.51	7.40	37513	2099	8.39	113.38	5.60	0.52	39.40	39.45	5.72	13.91	0.57	0.33	0.10
Lan Saka	349.54	15.24	4.40	40900	1479	4.23	97.02	3.62	2.10	46.79	31.58	5.07	13.79	0.34	0.27	0.07
Chawang	439.50	27.65	6.30	67293	3650	8.30	132.01	5.42	1.81	44.03	32.49	6.30	13.89	0.41	1.04	0.03
Phipun	501.18	11.86	2.40	29226	1812	3.62	152.74	6.20	1.77	51.27	32.62	6.07	6.40	0.72	0.77	0.39
Chian Yai	326.05	32.86	10.10	43457	2276	6.98	69.25	5.24	4.66	39.02	34.18	10.76	10.24	0.40	0.66	0.09
Cha-uat	760.30	53.01	7.00	86507	5335	7.02	100.65	6.17	1.61	51.73	27.39	9.99	7.48	0.88	0.81	0.11
Tha Sala	424.03	54.22	12.80	113067	4347	10.25	80.18	3.84	1.29	42.44	34.55	9.71	10.77	0.51	0.62	0.12
Thung Song	922.19	66.13	7.20	160724	8138	8.82	123.05	5.06	1.09	44.25	31.13	10.72	11.53	0.53	0.71	0.05
Na Bon	210.68	15.23	7.20	26934	1986	9.43	130.42	7.37	0.96	58.61	21.25	8.61	9.62	0.35	0.60	0.00
Thung Yai	609.19	47.75	7.80	74317	5781	9.49	121.06	7.78	1.35	65.91	19.49	5.09	6.87	0.42	0.86	0.02
Pak Phanang	537.92	73.37	13.60	130160	6546	12.17	89.22	5.03	6.29	45.88	30.78	8.62	6.94	0.75	0.63	0.12
Ron Phibun	435.26	24.65	5.70	82031	1501	3.45	60.90	1.83	3.60	27.85	43.84	13.26	10.26	0.73	0.33	0.13
Sichon	698.17	50.94	7.30	88611	3052	4.37	59.92	3.44	2.92	28.21	33.91	10.94	23.03	0.43	0.46	0.10
Khanom	315.83	24.28	7.70	30393	2364	7.49	97.35	7.78	2.33	55.54	26.90	7.19	7.28	0.38	0.34	0.04
Hua Sai	442.98	44.31	10.00	66503	2881	6.50	65.03	4.33	4.37	48.14	32.87	8.82	4.30	0.62	0.80	0.07
Bang Khan	475.96	29.72	6.20	46914	1875	3.94	63.09	4.00	7.25	38.93	36.48	12.96	3.36	0.16	0.59	0.27
Tham Phannara	179.00	10.15	5.70	19177	889	4.97	87.62	4.64	2.02	41.17	26.32	21.48	8.10	0.67	0.22	0.00
Chulabhorn	233.58	16.14	6.90	31584	2231	9.55	138.20	7.06	1.08	37.38	29.54	18.69	12.01	0.54	0.76	0.00
Phra Phrom	151.07	29.95	19.80	43588	2880	19.06	96.15	6.61	2.95	48.19	30.21	10.35	7.26	0.35	0.59	0.10
Nopphitam	732.73	18.68	2.50	33320	1293	1.76	69.22	3.88	2.17	33.02	34.42	9.44	18.95	1.39	0.54	0.08
Chang Klang	276.62	10.90	3.90	29909	839	3.03	76.97	2.81	1.55	61.98	25.15	5.24	4.53	0.60	0.95	0.00
Chaloem Phra Kiet	183.34	21.09	11.50	31572	1440	7.85	68.29	4.56	6.53	33.33	36.94	18.26	3.47	0.76	0.56	0.14
Summary	Total: 10,019.83	Total: 808.14	mean: 8.40 median: 7.20 SD: 4.57	Total: 1,585,030	Total: 84,609	mean: 8.52 median: 7.49 SD: 6.91	mean: 98.71 median: 96.15 SD: 32.56	mean: 5.20 median: 5.06 SD: 1.64	Relative proportion over entire province (%):							
									2.44	45.14	32.08	8.78	10.21	0.56	0.70	0.09

Table A.3 Areas, image coverage, population, containers data in district level in Krabi, Thailand

District Name	Area (km^2)	Area of image (km^2)	image coverage (%)	Population	Number of containers	Containers per km^2 land	Containers per km^2 image area	Containers per 100 population
Mueang Krabi	887.13	52.48	5.92	118288	2597	2.93	49.48	2.20
Khao Phanom	861.73	44.41	5.15	54956	3367	3.91	75.81	6.13
Ko Lanta	249.33	18.85	7.56	34337	1471	5.90	78.03	4.28
Khlong Thom	1132.32	70.66	6.24	76798	5339	4.72	75.56	6.95
Ao Luek	801.07	58.98	7.36	56138	5587	6.97	94.73	9.95
Plai Phraya	536.93	42.75	7.96	38578	2803	5.22	65.57	7.27
Lam Thap	285.40	19.75	6.92	24202	2367	8.29	119.83	9.78
Nuea Khlong	479.82	54.53	11.36	62634	6494	13.53	119.09	10.37
Summary	Total: 5,233.73	Total: 362.41	mean: 7.31 median: 7.14 SD: 1.88	Total: 465,931	Total: 30,025	mean: 6.43 median: 5.56 SD: 3.33	mean: 84.76 median: 76.92 SD: 24.87	mean: 7.12 median: 7.11 SD: 2.90

District Name	Relative proportions of container types (%)							
	Jar	Bucket	Potted plant	Tire	Bin	Bowl	Misc short open	Misc long open
Mueang Krabi	3.20	46.17	34.39	10.47	3.97	0.69	0.85	0.27
Khao Phanom	4.34	47.46	30.35	8.64	8.32	0.12	0.71	0.06
Ko Lanta	1.70	61.52	24.81	6.59	3.20	0.61	1.43	0.14
Khlong Thom	2.53	53.81	25.75	10.62	5.84	0.49	0.82	0.13
Ao Luek	3.11	48.31	26.69	9.68	10.90	0.34	0.84	0.13
Plai Phraya	4.50	49.30	30.07	6.35	8.46	0.36	0.71	0.25
Lam Thap	2.83	47.36	31.77	8.37	8.45	0.55	0.51	0.17
Nuea Khlong	1.45	60.32	23.61	7.13	5.99	0.48	0.95	0.08
	Relative proportion over entire province (%):							
Summary	2.83	52.27	27.56	8.68	7.25	0.43	0.84	0.14

Table A.4 Statistic of detected breeding sites corresponding to sub-districts where BI values were collected during dengue season.

District Name	Subdistrict Name	Area (km^2)	Area of image (km^2)	image coverage (%)	Population	Number of containers	Containers per km^2 land	Containers per km^2 image area	Breeding site per 100 population	Relative proportion of BS types (%): Jar	Bucket	Potted plant	Tire	Bin	Bowl	Misc short open	Misc long open
Mueang Nakhon Si Thammarat	Kamphaeng Sao	31.00	4.49	14.47	9559	865	27.90	192.65	9.05	0.12	56.65	21.73	4.86	15.84	0.23	0.46	0.12
Mueang Nakhon Si Thammarat	Chai Montri	14.87	3.78	25.42	6544	658	44.25	174.07	10.06	1.06	65.81	20.67	5.17	6.84	0.00	0.46	0.00
Mueang Nakhon Si Thammarat	Mamuang Song Ton	7.89	2.10	26.64	5013	313	39.67	149.05	6.24	5.11	27.80	40.58	8.31	17.57	0.64	0.00	0.00
Chawang	Na Wae	36.61	3.23	8.83	7372	472	12.89	146.13	6.40	1.69	51.48	30.93	7.63	6.14	0.42	1.69	0.00
Chawang	Huai Prik	66.31	3.23	4.87	6512	434	6.55	134.37	6.66	1.84	52.76	26.27	6.45	11.06	0.23	1.38	0.00
Chawang	Na Khliang	19.94	1.16	5.82	2845	278	13.94	239.66	9.77	2.16	39.21	27.70	6.12	23.38	0.00	1.44	0.00
Phipun	Kathun	121.62	3.62	2.98	5540	483	3.97	133.43	8.72	2.07	49.28	33.13	6.63	5.38	2.28	0.83	0.41
Cha-uat	Cha-Uat	72.46	8.24	11.37	12683	639	8.82	77.55	5.04	2.19	51.49	31.30	7.20	5.79	0.78	1.10	0.16
Cha-uat	Tha Pracha	27.56	3.71	13.46	7227	426	15.46	114.82	5.89	1.88	30.52	30.52	7.28	26.29	1.64	1.64	0.23
Cha-uat	Wang Ang	126.69	3.73	2.95	10304	531	4.19	142.36	5.15	0.56	33.52	27.50	21.28	14.31	1.13	1.69	0.00
Cha-uat	Ban Tun	82.70	6.57	7.95	7133	340	4.11	51.75	4.77	2.65	50.00	35.88	9.41	1.18	0.29	0.59	0.00
Cha-uat	Khon Hat	60.45	5.27	8.72	5908	423	7.00	80.27	7.16	1.89	63.36	24.82	6.86	0.71	1.18	0.95	0.24
Cha-uat	Ko Khan	42.53	3.52	8.28	8989	153	3.60	43.47	1.70	0.00	33.33	29.41	26.14	9.80	1.31	0.00	0.00
Cha-uat	Khuan Nong Hong	39.78	5.36	13.48	7327	766	19.26	142.91	10.45	1.96	42.69	26.24	17.10	10.57	0.78	0.65	0.00
Cha-uat	Khao Phra Thong	53.88	2.78	5.17	8152	153	2.84	55.04	1.88	0.00	33.33	29.41	26.14	9.80	1.31	0.00	0.00
Thung Song	Nong Hong	27.05	3.04	11.25	11010	470	17.38	154.61	4.27	0.64	34.89	27.23	12.34	23.83	0.43	0.64	0.00
Thung Song	Khao Ro	88.96	7.02	7.89	10575	244	2.74	34.76	2.31	2.05	18.85	65.16	10.66	2.87	0.00	0.41	0.00
Thung Song	Thi Wang	79.99	5.40	6.75	13912	723	9.04	133.89	5.20	0.55	65.42	20.06	10.37	2.90	0.14	0.55	0.00
Thung Song	Na Pho	30.89	4.45	14.42	6304	621	20.10	139.55	9.85	1.61	31.56	28.50	12.24	24.80	0.64	0.64	0.00
Na Bon	Kaeo Saen	68.30	6.73	9.85	7125	504	7.38	74.89	7.07	0.60	47.02	26.98	13.29	10.52	0.99	0.60	0.00
Thung Yai	Thung Sang	63.14	7.05	11.16	5620	510	8.08	72.34	9.07	1.57	41.76	24.51	4.71	25.10	0.78	1.57	0.00
Thung Yai	Kurae	84.83	5.97	7.04	8142	757	8.92	126.80	9.30	1.45	73.98	18.49	3.30	1.98	0.26	0.53	0.00
Thung Yai	Krung Yan	115.96	7.27	6.27	10583	903	7.79	124.21	8.53	2.10	73.53	18.05	2.33	2.88	0.44	0.66	0.00
Bang Khan	Bang Khan	158.87	9.90	6.23	13973	433	2.73	43.74	3.10	8.78	28.87	43.42	13.16	4.85	0.23	0.69	0.00
Bang Khan	Ban Lamnao	168.00	8.85	5.27	16284	918	5.46	103.73	5.64	6.10	49.46	31.05	9.80	2.61	0.11	0.54	0.33
Bang Khan	Wang Hin	76.25	6.28	8.24	9002	327	4.29	52.07	3.63	4.89	26.30	39.76	23.24	4.59	0.31	0.61	0.31
Bang Khan	Ban Nikhom	72.84	4.69	6.44	7655	197	2.70	42.00	2.57	13.20	32.99	41.12	10.15	1.52	0.00	0.51	0.51
Chulabhorn	Thung Pho	74.07	6.50	8.78	9776	919	12.41	141.38	9.40	1.09	42.00	26.22	13.60	15.78	0.44	0.87	0.00
Chulabhorn	Na Mo Bun	59.54	3.89	6.53	7146	527	8.85	135.48	7.37	1.14	36.05	30.55	21.25	9.49	0.76	0.76	0.00
Summary		Total: 1,972.98	Total: 147.83	mean: 9.54 median: 8.24 SD: 5.53	Total: 248,215	Total: 14,987	mean: 11.46 med: 8.08 SD: 10.46	mean: 112.31 med: 126.80 SD: 50.98	mean: 6.42 med: 6.40 SD: 2.69	Relative proportion over 29 sub-districts (%): 2.31	47.46	28.42	10.53	9.81	0.59	0.81	0.07

Table A.5 Container statistics for Lansaka district of Nakhon Si Thammarat.

District Name	Subdistrict Name	Area (km^2)	Area of image (km^2)	Image coverage (%)	Population	Number of containers	Containers per km^2 land	Containers per km^2 image area	Containers per 100 pop
Lan Saka	Khao Kaeo	86.48	1.20	1.39	7620	24	0.28	20.00	0.31
Lan Saka	Kamlon	96.43	2.72	2.82	9125	318	3.30	116.91	3.48
Lan Saka	Tha Di	35.49	2.56	7.21	7974	445	12.54	173.83	5.58
Lan Saka	Khun Thale	51.88	6.07	11.70	10296	446	8.60	73.48	4.33
Lan Saka	Lan Saka	79.27	2.69	3.39	5885	246	3.10	91.45	4.18
Summary		Total: 349.54	Total: 15.24	mean: 5.30 median: 3.39 SD: 4.17	Total: 40,900	Total: 1,479	mean: 5.56 median: 3.30 SD: 4.92	mean: 95.13 median: 91.45 SD: 56.56	mean: 3.58 median: 4.18 SD: 1.98

Relative proportion of container types (%)							
Jar	Bucket	Potted plant	Tire	Bin	Bowl	Misc short open	Misc long open
0.00	45.83	37.50	4.17	12.50	0.00	0.00	0.00
1.89	46.23	37.11	3.46	10.06	0.63	0.31	0.31
0.90	52.58	28.09	4.27	13.71	0.22	0.22	0.00
3.59	47.76	30.04	8.74	8.97	0.45	0.45	0.00
2.03	35.37	32.93	2.03	27.64	0.00	0.00	0.00
Relative proportion over entire district (%):							
2.10	46.79	31.58	5.07	13.79	0.34	0.27	0.07