IMAGE DETECTION OF MOSQUITO OUTDOOR BREEDING GROUNDS FOR ENHANCED DENGUE VECTOR SURVEILLANCE IN SONGKHLA PROVINCE, SOUTHERN THAILAND

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ABSTRACT: This research employs Outdoor Breeding Grounds Detection with Mask R-CNN to pinpoint mosquito breeding grounds in Songkhla Province, Southern Thailand, utilizing Google Street View imagery. Vector Surveillance was also conducted to analyse spatial distribution patterns of dengue fever patients and potential breeding sites. The Mask R-CNN algorithm achieved an accuracy of 77.5%, identifying 4,618 containers from 3,190 images, with car tires as the predominant breeding sites. Spatial analysis revealed clustered dengue fever cases in Hat Yai and Songkhla District, emphasizing the need for targeted interventions. The study identified two types of clustering: Type 1 with high urbanization and population density, and Type 2 in outbreak-affected sub-districts, often bordering similarly affected areas. These outbreak zones were community-centric, sharing environmental and lifestyle traits. Communal activities facilitated virus spread and local amplification. Focusing on these areas allows health authorities to effectively manage outbreaks and enhance prevention in Songkhla Province. These insights bolster vector surveillance and informed decision-making for dengue control in Southern Thailand.

1. INTRODUCTION

1.1 Background

The idea of sustainable development emerged in the 1970s to create a greener and fairer world. In 2015, the "UN Sustainable Development Goals-SDGs" were introduced, and one of the goals aimed at ensuring good health for everyone. An interesting project called The World Mosquito Program fights diseases like dengue and chikungunya, which are big concerns in many places. Dengue fever is a worry in over 100 countries and affects nearly 40% of the global population. Keeping people healthy is important, and preventing diseases carried by mosquitoes is a key part of this effort. (Word Mosquito Program, 2022)

In Thailand, there were 6,646 cases of dengue fever, with the highest number in Health Region 12, including places like Songkhla, Satun, Trang, Phatthalung, Pattani, Yala, and Narathiwat. The Southern region of Thailand has seen many cases of dengue from 2017 to 2021. In Mueang Songkhla District and Hat Yai District in Songkhla Province, dengue fever is a significant problem. It makes people sick and can spread quickly. (Department of disease control, 2022) The government aims to fight it by getting rid of places where mosquitoes lay eggs. An aim for the vector surveillance is try to track the population and behaviour of these vectors, often mosquitoes, to better understand their distribution, abundance, and potential risk of disease transmission.

Currently, dengue fever control can be categorized into two main types: the first is preventing disease occurrence, this primarily involves controlling the breeding sites of mosquito larvae. (Wanto W, et al 2017) Surveillance efforts target communities with a history of regular disease occurrence, focusing on Aedes mosquito habitats. The second is controlling disease outbreaks, this approach canters on mitigating outbreaks by employing adult mosquito control measures to prevent mosquito bites. This is implemented in areas where the disease is prevalent to minimize its spread and transmission. Thailand's dengue control strategy encompasses these measures. The key emphasis lies in monitoring and eliminating Aedes mosquito breeding sites, along with implementing adult mosquito control measures during dengue outbreaks (Office of Disease Prevention and Control No. 9, 2016). Containers inside houses where mosquitoes lay eggs are usually well-kept to prevent dengue. However, outdoor containers can be a problem. When the owner is unknown, they might get neglected and become a breeding site for Aedes mosquitoes. Mosquitoes have a short lifespan, typically less than two months. Most mosquito species tend to stay close to their breeding areas. For instance, Aedes aegypti and Aedes albopictus, which can carry diseases like Dengue and Zika, typically have a range of only a few hundred feet (30.48 meters) from their breeding grounds. On the other hand, many other mosquito species can travel up to 3 miles or 4.8

kilometers from their breeding areas. (MosquitoNix, 2023) If a house or person is within this range, there is a risk of contracting dengue fever.

However, locating all these places is challenging, especially in large areas. This task is carried out by public health volunteers who visit households to educate residents about managing waterlogged containers or provide abet sand to hinder mosquito breeding. While this approach is valuable, it can be time-consuming and may not always yield comprehensive results. Indeed, having precise information about the location of containers is crucial for more effective disease control measures. Various studies explore using new technology to address this issue. For instance, Haddawy et al. (2019) introduced an innovative method to identify potential dengue vector breeding sites in geotagged images from Google Street View. This involved using a convolutional neural network to detect eight common containers with an impressive accuracy of 0.91 (F-score) in testing. The container counts obtained through Google Street View align closely with manual surveys. Moreover, results from regression analysis linking container densities to larval survey data exhibit a strong predictive power for Breteau index values during the dengue season (R-squared of 0.674). The significance of this container density data in risk prediction remains an ongoing inquiry. Ananthajothy G. and et al., (2023) conducted a study introducing a technological solution to assist public health inspectors in automating the detection of potential mosquito breeding sites using drone imagery. Two strategies, namely Convolutional Neural Network (CNN) and Few-Shot Learning (FSL), were compared for this task. The research utilized a supervised learning approach with a labeled custom dataset of aerial images to train the models. The CNN achieved the highest testing accuracy of 84.29% after 100 epochs of training, whereas FSL attained only 79% accuracy after 2000 epochs. In conclusion, the proposed CNN-based system shows promise in aiding local health agents to identify potential mosquito breeding sites, particularly those that are inaccessible to humans.

This is where new technology comes into play. A smart approach known as Mask R-CNN which stands for "Mask Region Convolutional Neural Network." (Gkioxari et al., 2018) The Mask R-CNN method is a computer vision technique used for object detection and instance segmentation tasks. It extends the Faster R-CNN architecture by adding an additional branch that predicts pixel-level masks for each detected object. This allows not only identifying objects but also segmenting them within the image. Mask R-CNN is widely used in various fields, such as object detection, instance segmentation, and even applications like medical image analysis and autonomous driving, where precise object localization and segmentation are crucial. (Renu K., 2022)

Finding the containers where mosquitoes may breed by using object detection method with street view images help identify potential mosquito breeding spots. With this technology, the effort is to identify and count potential mosquito breeding sites in these districts. The aim of this research is to investigate the distribution of containers that could serve as breeding sites for mosquitoes and the occurrence of dengue fever cases. The findings from this study could provide valuable insights for enhancing dengue control policies, including interventions like distributing larvicide or implementing targeted clean-up measures in areas with identified mosquito breeding containers. This could be especially valuable in situations where there are limited manpower and budget constraints for conducting extensive surveys.

1.2 Study Areas

The study area for this research covers Mueang Songkhla District and Hat Yai District in Songkhla Province, Thailand. This study utilizes patient information from the year 2019, sourced from the Office of Disease Prevention and Control 12 in Songkhla Province. The street view imageries for finding outdoor containers were downloaded as a file in the year 2019 as well.

Figure 1. Study Area: Muang Songkhla and Hat Yai

2. METHODOLOGY

2.1 Mask R CNN

Object detection in computer vision localizes and classifies objects in images. Mask R-CNN, developed in 2017, excels in recognition, detection, and segmentation, offering speed and accuracy. It follows two steps: proposing regions and generating boundary boxes, then producing masks aligned with predictions. (Renu, 2019) This versatility makes it popular. This study uses Mask R-CNN to detect the containers that potentially serve as breeding sites for mosquitoes. The containers, or outdoor breeding ground images, are sourced from Google Street View images. The breeding grounds are categorized into five distinct classes: rubbish bin, plant pot, water jar, car tires, and big earthen jar (Figure2).

Figure 2. five categories of breeding grounds.

In this study, the evaluation of accuracy involves using a confusion matrix (Figure 3), which plays a crucial role in assessing classification problems (Ananthajothy G. and et.al 2023). The metrics for assessing detection performance are as follows:

True Positive (TP): Program predicts true and actual result is true.
True Negative (TN): Program predicts false and actual result is false.
False Positive (FP): Program predicts true but actual result is false.
False Negative (FN): Program predicts false but actual result is true.

		Actual	
		Positive	Negative
Predicted	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Figure 3. Confusion matrix.

The objective is to achieve accuracy and precision both exceeding 90%, along with recall, while detecting breeding grounds. These metrics serve as key performance indicators and acceptance criteria. Certainly, here are the equations for calculating Accuracy, Recall (Sensitivity), Precision (Positive Predictive Value), and F1-score (Harmonic Mean of Precision and Recall): using the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values: (Ananthajothy G. and et.al 2023)

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

F1-score = 2 * (Precision * Recall) / (Precision + Recall) (4)

Once we have acquired the image, we proceed to locate the coordinates of the subject within it. This is achieved through the use of a pinpoint application on an online platform, which provides us with both latitude and longitude. Additionally, the platform offers a Batch Service feature, enabling the conversion of multiple addresses into GPS coordinates all at once

2.2 Nearest Neighbour Index-NNI

The measure of dispersion resembles a point's distribution presented as an index known as the Nearest Neighbour Index. This index ranges from 0 to 2.5. A value of 0 suggests scattered clustering, while a value close to 1 signifies a uniform distribution. When the index approaches 2.15, it indicates an organized distribution. The Average Nearest Neighbor tool in Geographic Information System provides five values: Observed Mean Distance, Expected Mean Distance, Nearest Neighbor Index, z-score, and p-value. These values are displayed as messages in the Geoprocessing pane during tool execution and can be used as output values for models or scripts. (Marceló-Díaz, C and et,al. 2023)

3. RESULTS AND DISCUSSION

3.1 Outdoor Breeding Grounds Detection Using Mask R-CNN

3.1.1 Mosquito breeding grounds finding

In order to evaluate the precision of object detection via Mask R-CNN, images of containers employed in the study were gathered from Google Street View. These images were categorized into five groups: rubbish bin, plant pot, water jar, car tires and big earthen jar. The collected images were then subjected to processing, yielding the count of each container type identified in the photos. A total 7,759 container images were sourced from Google Street View, revealing 4,618 detected containers within TP. Notably, among these, 1,364 were mosquito breeding containers located in the Mueang Songkhla District and 3,254 located in Hat Yai district. A majority of them, exceeding 60 percent, consist of discarded tires.

During the experimentation phase of the program designed for object detection, the system outlines object types and associated probabilities. This study focuses on categorizing container groups into five distinct classes, as mentioned earlier. The program subsequently generates masks, assigning numerical probabilities to the likelihood of an object being appropriately masked. As depicted in Fig. 5, the masked objects are then subjected to testing. These metrics provide a measure of the performance of the object detection system:

- Accuracy of 77.5%: This means that roughly three-fourths of the detected objects were correctly identified. While this might be considered good in some scenarios, it could be improved further.
- Precision of 83.0%: This suggests that out of the objects identified as positive, the system was correct around 83% of the time. This is a reasonably good precision rate.

- Recall of 85.2%: This indicates that the system was able to capture about 85% of all actual positive objects in the dataset. A higher recall is generally desirable, but 85.2% is still a respectable value.
- F1-score of 84.0%: The F1-score takes into account both precision and recall. An F1-score of 84.0% suggests a good balance between these two metrics.

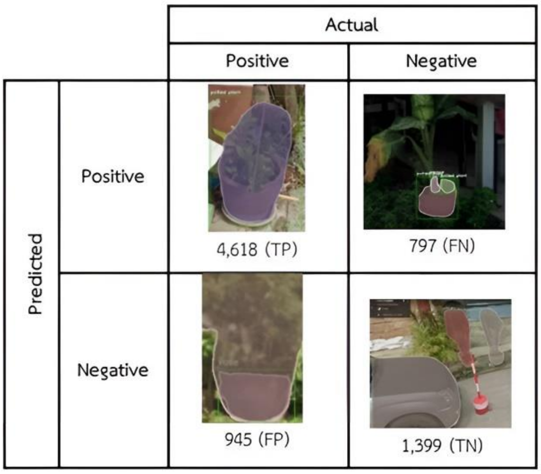


Figure 4. Confusion matrix.

Absolutely, if the application is breeding grounds detection, the achieved results seem promising and could indeed be acceptable. Detecting breeding grounds likely involves identifying patterns and objects within images or data, which might not require the same level of precision and recall as critical applications like medical diagnoses or autonomous driving.

3.1.2 The spatial distribution of mosquito breeding grounds

After obtaining the image of objects, the coordinates of the objects within it are determined. This is done by using a pinpoint application on an online website to obtain latitude and longitude. The website also offers a Batch Service function, allowing for the conversion of multiple addresses into GPS coordinates simultaneously. This section provides information on the distribution of outdoor containers that were detectable and identifiable in Mueang Songkhla district and Hat Yai district in the year 2019. In Mueang Songkhla district, a total of 1,364 outdoor containers were identified as mosquito breeding sites. Among these, 59.97% were tires, 18.98% were water jars, 9.02% were plant pots, 7.13% were rubbish cans, and 4.98% were big earthen jars. In the Hat Yai district, there were 3,254 outdoor containers. Of these, the majority of containers, specifically 59.98% of all containers, were tires, while the least common type of container was big earthen jars, accounting for only 4.98% of the total (Figure 5).

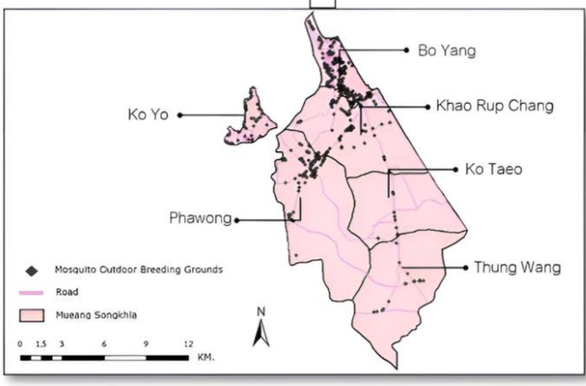
Based on the research findings, the spatial distribution of mosquito breeding site containers in Mueang Songkhla District demonstrates a clustered pattern. The Nearest Neighbor Index (NNI) for this analysis was determined to be 0.34, Z-Score was -26.84 and P-Value was 0.00 signifying a notable degree of clustering. It was observed that the majority of these containers are grouped closely together within sub-districts characterized by a high population density, such as Bo Yang Subdistrict and Khao Rup Chang Subdistrict, among others as show in figure 5.

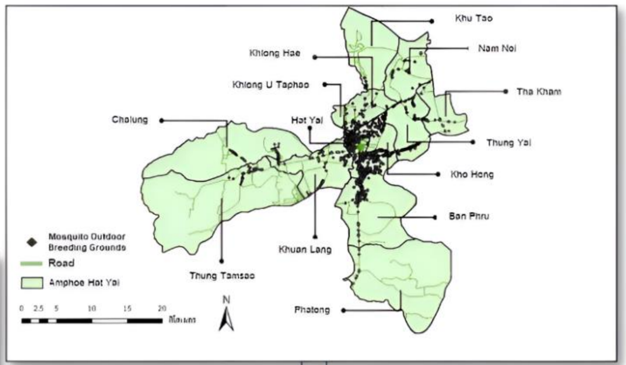
In Hat Yai district, a similar clustered spatial distribution was observed, with a calculated Nearest Neighbor Index (NNI) of 0.155, Critical Value (Z-Score) was calculated to be -26.82, and the associated Significance Level (P-Value) was 0.00 reaffirming the prevalence of clustering in this area as well. The predominant containers identified are tires. The spatial distribution of mosquito breeding sites in Hat Yai district is illustrated in Figure 5 on the right-hand side. The majority of containers are clustered in Hat Yai sub-district, which shares its name with the district. Additionally, containers are distributed outward to the surrounding area, extending between the junction of Kho Hong and Khuan Lang sub-districts. Similar to Mueang Songkhla district, tires are the most frequently detected containers, reflecting the efficiency of the Mask R-CNN program in identifying them. It is recommended to prioritize the handling of tire containers due to their prevalence.

The existence of mosquito breeding containers is especially higher in densely populated urban areas. This is a direct result of the larger number of residents, which leads to a greater density of these containers. The close proximity of people and increased human activity in urban settings often results in more discarded items, containers, and potential breeding sites for mosquitoes. As a result, urban areas tend to display a higher concentration of such containers compared to less densely populated regions.

Containers advantageous to mosquito breeding are more frequently encountered in densely populated urban areas, resulting in a higher concentration of such containers. On the contrary, areas with lower population densities, such as rural, agricultural, and mountainous regions like Koh Taeo and Thung Wang subdistricts in Mueang Songkhla District, tend to have fewer instances of mosquito breeding containers. Specific areas like Thung Tamsao Subdistrict in Hat Yai, as well as Phatong Sub-district, Khu Tao Sub-district, Khlong U-Tapao Sub-district, Khlong Hae, and Thakham, are primarily agricultural in nature and may also face challenges in accessing Google Street View data due to their unique geographical characteristics.

Container Types	Number	percentage
water jar	259	18.988
car tires	818	59.971
plant pot	123	9.020
rubbish bin	96	7.138
big earthen jar	68	4.985
Total	1364	100





Container Types	Number	percentage
water jar	618	18.992
car tires	1952	59.988
plant pot	293	9.034
rubbish bin	260	7.991
big earthen jar	130	3.995
Total	3254	100

Figure 5. Potential breeding containers distribution in Mueang Songkhla District (left) and Hat Yai District (right)

The main items in outdoor areas, such as discarded items, containers, building materials, and flowerpots, were particularly noticeable as potential breeding sites for mosquito larvae and pupae. Ornamental plants and water storage tanks were also commonly found, confirming previous observations. Therefore, it is crucial to educate the community about the importance of regularly emptying, removing, or covering these types of containers. (Louis, V. R. and et al., 2016 and Sarfraz, M. S. and etal., 2012)

Although our study did not directly identify containers with mosquito larvae, many studies have established a clear link between outdoor containers and the presence of mosquito larvae. For instance, in Justin Stoler's research (2011), out of 477 wet containers examined, 46.3% were found to be hosting mosquito larvae, underscoring the significant association between containers and mosquito infestation.

Another study focused on Aedes aegypti breeding habitats in Ouagadougou City, Burkina Faso, Africa. They examined a total of 1061 container breeding sites, and found that 760 of them (classified as 'positive' containers) contained immature stages of Ae. aegypti. When considering container types, tires were identified as the most frequently encountered potential breeding site, followed by large and then medium container types. (Ouédraogo, W. et al., 2022)

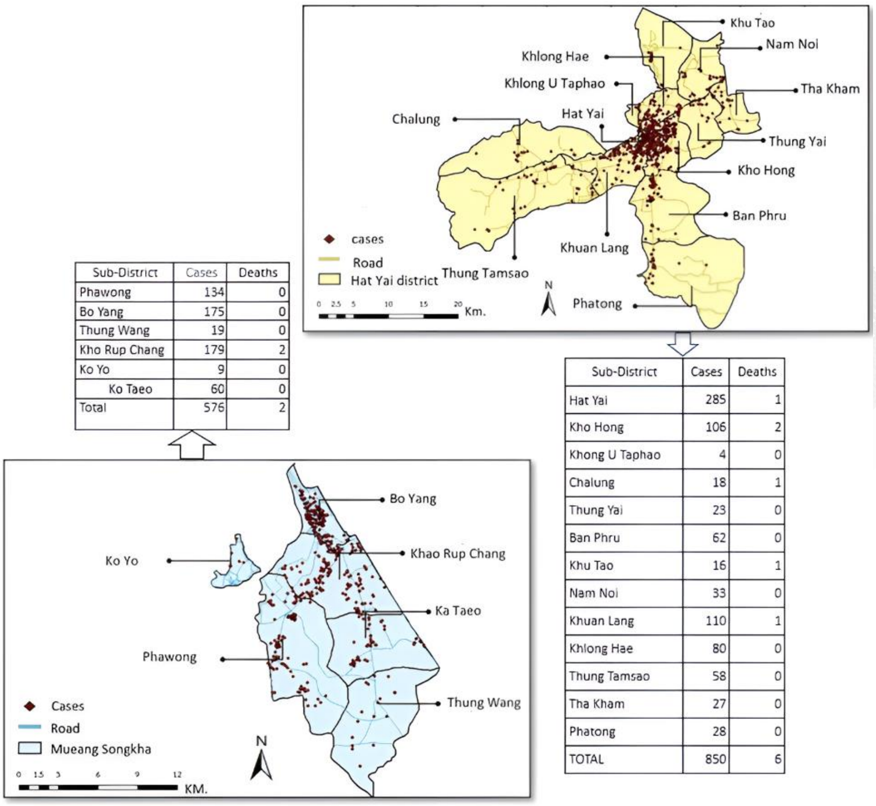
Similarly, research on Aedes mosquito distribution in Cameroon revealed a diverse range of breeding habitats. Aedes larvae were predominantly found in tires (41.68%), followed by plastic containers (33.99%). Additionally, Ae. albopictus larvae were primarily discovered in discarded tires (42.51%). (Djiappi-Tchamen B. etal., 2021)

3.2 Dengue Cases Spatial Distribution Pattern

In 2019, Mueang Songkhla District, situated within Songkhla Province, experienced dengue fever outbreaks across three districts. Among the six sub-districts affected, Khao Rup Chang, Po Wong, and Koh Taeo sub-districts collectively accounted for 50% of cases. Notably, Khao Rup Chang reported the highest incidence with 179 cases, resulting in two fatalities. This sub-district also hosts a municipal government and exhibits a population density of 1,562.10 individuals per square kilometer. Bo Yang Subdistrict, encompassed within the Songkhla Municipal Administrative Area, recorded 175 cases and boasts a population density of 6,882.08 persons per square kilometer. Importantly, these two areas form a contiguous zone. Furthermore, Phawong (815.86 persons per square kilometer) and Koh Taeo (400.28 persons per square kilometer) experienced lower population densities, yet still reported distinguished case counts of 134 and 60, respectively.

The analysis of dengue patient data, using the Average Nearest Neighbor (NNI) method, revealed a NNI value of 0.44. This indicates a significant spatial distribution pattern. The Critical Value (Z-Score) was calculated to be -22.84, and the associated Significance Level (P-Value) was 0.00. This suggests a highly clustered pattern of dengue fever cases in Hat Yai, Songkhla Province.

In Hat Yai District, dengue outbreaks were identified in three sub-districts, comprising 98 villages or 23.08% of the district. These sub-districts were Thung Tamsao, Thung Yai, and Hat Yai. Among these, Hat Yai reported the highest number of cases with 285 confirmed cases and one fatality. In Hat Yai, the traditional village system has been abolished, and instead, there exists a local governing body known as Hat Yai Municipality, with a notably high population density of 7,582.52 persons per square kilometer. Thung Tamsao operates under a municipal government and has a population density of 146.81 individuals per square kilometer, with 58 confirmed cases. Thung Yai Subdistrict is administered by an administrative organization and has a population density of 131.26 persons per square kilometer, with 23 confirmed cases.



Sub-District	Cases	Deaths
Phawong	134	0
Bo Yang	175	0
Thung Wang	19	0
Kho Rup Chang	179	2
Ko Yo	9	0
Ko Taeo	60	0
Total	576	2

Sub-District	Cases	Deaths
Hat Yai	285	1
Kho Hong	106	2
Khong U Taphao	4	0
Chalung	18	1
Thung Yai	23	0
Ban Phru	62	0
Khu Tao	16	1
Nam Noi	33	0
Khuan Lang	110	1
Khlong Hae	80	0
Thung Tamsao	58	0
Tha Kham	27	0
Phatong	28	0
TOTAL	850	6

Figure 6. Dengue Cases Spatial Distribution in Mueang Songkhla District (left) and Hat Yai District (right)

The analysis of dengue patient data, using the Average Nearest Neighbor (NNI) method, revealed a NNI value of 0.36. This indicates a significant spatial distribution pattern. The Critical Value (Z-Score) was calculated to be -33.53, and the associated Significance Level (P-Value) was 0.00. This suggests a highly clustered pattern of dengue fever cases in Hat Yai, Songkhla Province

The study's findings reveal two distinct types of clustering in the spatial distribution model of dengue patients in Mueang Songkhla and Hat Yai districts in 2019:

Type 1 clusters are characterized by a large population, high population density, and a highly urbanized environment. Examples of such sub-districts include Hat Yai Subdistrict, Tambon Khohong, Tambon Bo Yang Khao, Rup Chang Subdistrict, among others.

Type 2 clusters are observed in sub-districts experiencing dengue outbreaks, often aligning with the boundaries of neighbouring sub-districts also affected by outbreaks. Sub-districts like Koh Taeo, Phawong, Thung Yai, and Thung Tamsao were notable examples. These outbreak areas were predominantly community-centric, where neighbouring regions tended to share similar environmental, social, cultural, and lifestyle characteristics. Moreover, frequent communal activities like those in schools, markets, workplaces, etc., contributed to significant population movement, acting as a crucial factor in both the spread of the virus to other areas and the amplification of infections within residential zones.

This pattern is consistent with the research conducted by Theeravadi Kopayakin et al. (2018) on "Spatial Correlation of Dengue Fever at Tak Village, 2014-2016," which similarly noted that clusters of dengue fever cases tend to occur in urban and commercial areas.

The investigation into the correlation between outdoor breeding ground distribution and the distribution of dengue cases, using overlay data, revealed a consistent spatial distribution pattern in the same area. In their 2014 study, Piet F.M. Verdonschot and Anna A. Besse-Lototskaya examined the flight distances of mosquitoes and presented the following findings: Aedes notoscriptus can fly less than 500 meters, Aedes albopictus can cover a distance of 500-1000 meters, and Aedes vexans is capable of flying more than 4000 meters. In their 2022 study, Thomas C. Moore and Heidi E. Brown estimated the flight distance of Aedes aegypti and determined that, on average, Ae. aegypti covers a distance of 105.69 meters. This measurement is influenced by factors like climate and degree of urbanization.

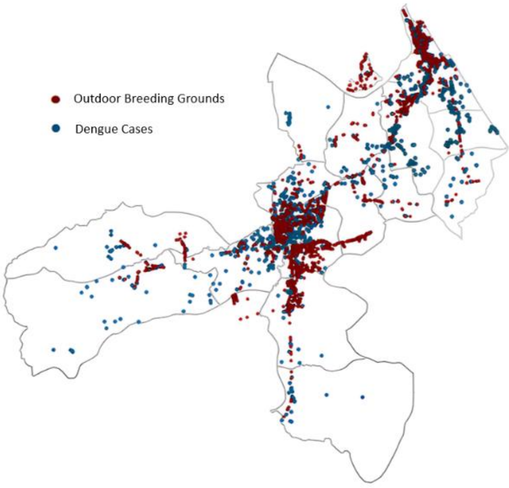


Figure 7. Association between Outdoor Breeding Ground Distribution and Dengue Case Distribution

This map in figure 7 of mosquito breeding sites and the number of cases confirms that it can be the primary information for surveillance of dengue outbreaks. Home breeding containers are taken care of by homeowners, but these containers outside the house that has no the owner, if located, can be managed to destroy or overturn them to prevent waterlogging. Faster prevention of dengue outbreaks.

4. CONCLUSION

In conclusion, the evaluation of Mask R-CNN's image processing accuracy demonstrated remarkable precision and recall rates, standing at approximately 85.2%. However, it is essential to acknowledge the model's limitations in identifying overlapping objects, resulting in slightly lower assessment outcomes with an overall accuracy rate of 77.5%. The effectiveness of Mask R-CNN in understanding messy laying containers is particularly pronounced in densely populated urban areas where objects tend to cluster closely together. This phenomenon is especially evident with containers serving as breeding grounds for mosquitoes, often found within human-inhabited regions. Conversely, areas with fewer mosquito breeding containers typically correspond to regions with lower population densities, such as rural, agricultural, and mountainous areas.

The study also identified that the majority of breeding containers are tires. Therefore, proper management of old tires, either through destruction or appropriate disposal, can significantly contribute to eliminating potential mosquito breeding sites. Moreover, the research highlights a consistent pattern in the disposal of containers and patients across similar localities. This finding holds great promise for enhancing outbreak surveillance efforts. Remarkably, outdoor areas are replete with potential breeding sites for mosquito larvae and pupae, including discarded items, containers, building materials, and flowerpots. Ornamental plants and water storage tanks also emerged as commonly found breeding sites, corroborating previous observations. Thus, community education regarding the regular emptying, removal, or covering of these types of containers is imperative in effective mosquito control efforts.

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