# Identifying Mosquito Breeding Sites via Drone Images

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## ABSTRACT

Public Health Inspectors (PHIs) in Sri Lanka are facing a problem of identifying certain mosquito breeding sites since they cannot easily reach places such as roof gutters, overhead water tanks, inaccessible rooftops and cement materials which are capable of retaining water. The goal of a such inspection of suspected sites is to reduce the number of dengue patients by eradicating dengue mosquito habitats.

Due to the retention of water in the aforementioned sites for a long period of time, those places tend to be full of lichens. In general, lichens are visible in dark color. This characteristic helps to identify prolonged water retention areas.

With the rapid advancement of technology, the drone has been created as one of the most cost effective apparatus to capture the places that a human cannot access.

With respect to the aforesaid context, this paper presents a simple and a novel approach to identify mosquito breeding sites via drone images. The proposed approach processes images captured from a drone to identify possible sites where stagnant water may retain and highlights if such areas are apparent within the image.

The evaluation process found that the proposed method, produces a satisfactory level of accuracy in identification of possible water retention areas and the final results depend on the drone camera tilt angle and the effect of shadows.

## Keywords

Drone Systems; Mosquito Breeding Sites; Dengue.

## 1. INTRODUCTION

Through cleaning the places with stagnant water, removing the landscape structures which support the mosquito breeding, usage of anti-mosquito valves, mosquito repellents, mosquito coils and mosquito nets can help to prevent mosquito bites. Nevertheless, there can be some places with stagnant water that humans cannot easily reach or identify (i.e. roof gutters, water tanks, inaccessible rooftops and cement materials which are capable of retaining water).

Due to the retention of water in those inaccessible sites for a long period of time, those places are usually covered with lichens. According to our observation, the lichens of these places contrast with the rest due to their dark color [1, 3]. This color specification is utilized for the identification of mosquito breeding sites in unreachable places as a help for the PHIs.

An Unmanned Aerial Vehicle (UAV), better known as a drone is popular in a wider range of audience, due to its maneuverability and smaller size relative to the other unmanned counterparts. Therefore, a drone can access and observe the places that a man cannot. Hence, this paper presents a solution to identify possible mosquito breeding places via aerial images.

## 2. RELATED WORK

We reviewed several Water Detection approaches to detect mosquito breeding sites. Water detection through material recognition and dynamic texture recognition with and without the use of a UAV are considered in this review.

Water in material recognition using videos without the use of UAVs is such an approach. This approach tries to shift from laboratory setting image databases to real-world image databases [10, 11, 17]. There are few limitations; it only investigates spatial characteristics and non-functioning temporal characteristics.

Dynamic texture recognition in videos is another water detection approach, which does not get the help of UAVs. Dynamic textures such as water, weather patterns and fire fall under the category of motions with either statistical or structural similarity in both space and time [13]. This approach is based on the optical flow statistics [9, 14, 15]. The influence of the noise, the optical flow representation directly affects the water detection and does not provide a proper solution.

Water identification in videos via UAVs such as using flying robots, maritime environments and autonomous driving systems is another popular approach [5, 6, 16]. These UAV systems provide accurate results in restricted environments [5, 6, 16].


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Nevertheless, they are not capable of providing a fully automatic water detection solution.

The problems with the above approaches have been addressed by Mettes et al., and they came up with another robust solution for water detection using videos. They have introduced a methodology to detect water through spatial and temporal dynamics of water [12]. However, this approach only discusses the identification of water, which spreads in a considerably huge area, and not merely for the water retention areas that a human cannot access.

Water detection with multiple cues based on texture, color and stereo range data is another approach and each detector is targeting on varied water characteristics [7]. Nevertheless, this approach is not detecting water retention areas as same as the aforementioned approach.

# 3. COLORATION OF WATER RETENTION AREAS

According to the observation, due to the reason of water remaining in the inaccessible sites for a long period of time, those places are characterized in dark color with the influence of lichens [1, 3]. This attribute helps to identify the possible water retention areas. Further analysis of the images in the water retention areas revealed that the usual coloration of the water retention areas is in between 8 to 15 in 8-bit per channel RGB (Red-Green-Blue) ratio and the intensity values are between 75 to 150 in 8-bit per channel RGB values. This color range is a strong evidence for identifying the water retention areas that a man cannot access, and it can be used for identifying probable mosquito breeding places.

# 4. SYSTEM OVERVIEW

The proposed methodology is focused on flying the drone, according to the PHI's requested area. After that the images of that area are captured via drone and the map of the possible mosquito breeding sites is generated. Figure 1 shows the system overview. According to the Figure 1, the system consists of basically sixteen steps as follows;

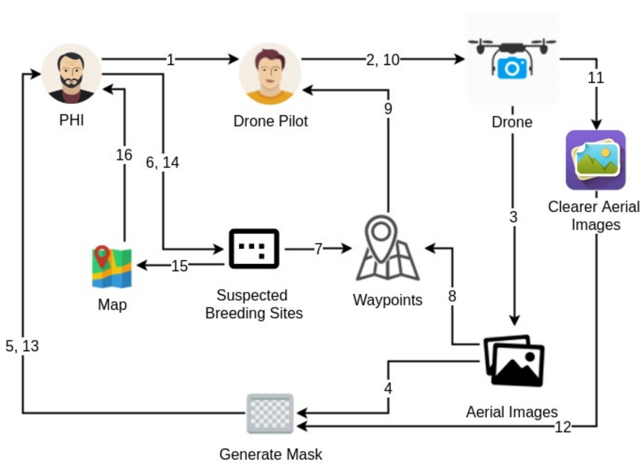


**Figure 1. System Overview**

## 4.1 Step 1

The PHI requests to the drone pilot to fly the drone over the area that he/she wants to observe to suppress mosquito breeding.

## 4.2 Step 2

The drone pilot flies the drone.

## 4.3 Step 3

He/ she collects the images of captured area.

## 4.4 Step 4

Possible water retention areas are identified in the collected input images via the "Possible Water Retention Area Identifier". It consists of two phases; "Thresholding" and "Merging".

### *4.4.1 Thresholding*

Initially, the system identifies possible water retention areas via its RGB values in the input images. After that, it highlights the possible water retention areas in a dark color and shows the other areas in white. Then, the thresholded image is sent to "Merging".

#### *4.4.1.1 Merging*

This phase integrates the original input image (which is taken from the drone) together with the thresholded image (which is getting from the "Thresholding" phase). The integrated image is sent to the PHI through the system.

## 4.5 Step 5

The set of images with the highlighted possible mosquito breeding sites is sent to the PHI.

## 4.6 Step 6

The PHI verifies the images that he/ she received, as the suspected breeding sites.

## 4.7 Step 7

The images of the suspected breeding sites use for the "Waypoints Generator" to generate the waypoints of the images with possible water retention areas.

## 4.8 Step 8

The input images in Step 3 are processed using WebODM and then 3D mesh is generated. The generated 3D meshes are used for the "Waypoints Generator".

## 4.9 Step 9

The drone pilot receives the generated waypoints and the generated heights of each suspected breeding site via the "Waypoint Generator". It uses the suspected breeding sites and the generated 3D meshes, to generate the geo locations of those sites and the height that the drone should fly from each site.

## 4.10 Step 10

The drone is flying in the path according to the received waypoints and the received heights by adding a 10m height to each height by the drone pilot.

## 4.11 Step 11

The drone pilot collects clearer images of the suspected breeding sites using the generated waypoints.

## 4.12 Step 12

Possible water retention areas are identified in the clearer images via the "Possible Water Retention Area Identifier" as in Step 4.

## 4.13 Step 13

Those images are sent to the PHI to identify suspected breeding sites as in Step 5.

## 4.14 Step 14

Again the PHI verifies the images that he/ she received as the suspected breeding sites.

## 4.15 Step 15

The map is generated for the possible mosquito breeding sites through geo coordinates of the second suspected breeding sites images via the "Map Generator". According to the geo coordinates of the second suspected breeding sites images, the system generates the map for the PHI with the possible mosquito breeding sites.

## 4.16 Step 16

The generated map is sent to the PHI. This map helps the PHI to suppress mosquito breeding in the places which are marked in the given map.

# 5. FIELD TEST

The drone pilot is required to fulfill several aspects when the drone is flying;

1. The drone pilot does not fly the drone in the rain, since the purpose is to capture only the water retention areas as they are the possible mosquito breeding sites, not the water flowing areas.
2. He/ she keeps the drone around at a 10m height from the top of the highest building in the capturing area at the first flight.
3. He/ she keeps the drone camera with 90° of downwards tilt from the drone. (The used drone and the used drone camera for the observation are DJI Phantom 4 and DJI FC330 respectively.)
4. He/ she flies the drone around 12.00 noon, so as to minimize the shadow effect, since that time in Sri Lanka the Sun's Angle of Elevation (AoE) and the Angle of Depression (AoD) are higher relative to the other times. If Sri Lankan Time (SLT) is before 12.00 noon or after 12.00 noon, the Sun's AoE and the AoD are lower compared to 12.00 noon from the shadow of an object. This aspect directly impacts on the nature of the shadow cast. [2]

This research has been conducted in towns, universities and hospitals respectively in Ambalangoda, Colombo and Karapitiya in Sri Lanka as a representation of urban and semi-urban areas with tropical and subtropical climates. The reason for minimizing the shadow effect is most of the time, the color of a shadow is extremely similar to the color of the possible sites where water can remain.

For the second time, the drone is flying through the received waypoints and the received heights over the each possible water retention area by adding a 10m height for each height. The reason for adding a 10m height for the received height is to improve the GPS (Global Positioning System) accuracy and maximize the camera capturing area.

# 6. EVALUATION AND RESULTS

The research mainly focused on identification the possible water retention areas via drone images where a human cannot access. The evaluation was carried out on multiple images in different urban and semi-urban areas with tropical and subtropical climates. We obtained Data Set 1 (DS1) from an urban area; Ambalangoda, Data Set 2 (DS2) from a university premises; Colombo and Data Set 3 (DS3) from a hospital area; Karapitiya. Each dataset is consisted of 50 images. Those data sets were collected during the first flights of the drone (Step 3 in Section 4).

We went through a set of images to identify possible water retention areas. Consequently, each image was segmented to same sizes of parts and examined whether the proposed system identifies a segmented part has water retention areas or not. For the final result we analyzed True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) counts.

In here, TP is the system which detects possible water retention area, and there is such area in the image segment. Similarly, with respect to the definitions of True Negative, False Positive and False Negative, remaining TN, FP and FN are defined accordingly in this context. Based on those metrics, recall and precision were derived.

The system was fed with DS1, DS2 and DS3 datasets separately and relevant metrics were reported for each dataset. According to the Table 1, DS2 shows higher recall and higher precision than the DS1 and DS3. The reasons for that in DS2 are the camera tilt of drone is higher and the flying time of drone is relatively closer to 12.00 noon in Sri Lankan Time than the DS1 and DS2 (Table 2). Since DS1's drone camera tilt is less than 90° and the flying time of drone is around 3.00 pm which gives lower results than DS2 (Table 1, Table 2). However, DS3 which has 90° of the drone camera tilt and the drone flying time is early than DS1, gives better results than DS1. However, DS3 gives lower results than DS2, since DS3's drone flying time is later than DS2's (Table 1, Table 2).

For obtaining better results, the drone camera tilt angle should be 90° and it should fly around 12.00 noon in Sri Lankan Time to minimize the shadow effect.

**Table 1. Recall and Precision values of DS1, DS2 and DS3**

| Dataset | Recall | Precision |
|---|---|---|
| DS1 | 73.23% | 42.68% |
| DS2 | 96.99% | 81.88% |
| DS3 | 91.38% | 81.54% |

**Table 2. Camera tilt, Drone flying time and the Sun's AoD values of DS1, DS2 and DS3**

| Dataset | Camera Tilt | Drone Flying time in SLT | The Sun's AoD |
|---|---|---|---|
| DS1 | 60° | 15:00 | 40.69° |
| DS2 | 90° | 13:30 | 60.55° |
| DS3 | 90° | 14:30 | 41.36° |

# 7. CONCLUSION

The main objective of this research was to come up with a mechanism to identify possible water retention areas in inaccessible places. Even though there are many methodologies according to the previous approaches (Section 2), they did not address an approach identify the possible water retention areas that a man cannot access. Through this research, we have come up with a solution to identify the possible water retention areas in unreachable locations, using the coloration of the images of those sites. This approach observes the places with lichens and then gives a highlighted image with the possible places of mosquito breeding for the use of PHIs.

The evaluation aimed to identify the accuracy of this approach by calculating recall and precision via set of drone images which are taken from urban and semi-urban areas with tropical and subtropical climates, since mosquitoes spread their authority in those areas. According to the results, the proposed approach is capable of identifying the possible mosquito breeding sites. Analyzing the impact of the camera angle and the shadows on the results, we propose to keep the camera tilt of the drone in 90° and fly the drone when the Sun's AoE and the AoD are relatively higher time from the shadow of an object to minimize the shadow effect.

Through this research, the identification of the possible water retention areas via drone images was introduced to detect mosquito breeding places. This proposed methodology is a cost effective and simple approach. This system can be used not only when the highlighted areas consist of water, but also when those areas do not consist of water, because we are only detecting the coloration of water retention areas not the water.

In future, we will release Bacillus thuringiensis israelensis (Bti) bacterias [8] to the water retention areas which are marked in the generated map (Step 14 in Section 4) via a drone flight. This attempt will help the PHI to eradicate mosquitoes.

Minimizing shadow effect and improving the current algorithms to detect other water retention areas that a human can access such as coconut shells, tyres are the other future attempts. Furthermore, the proposed approach in this paper can be replicated not only for suppressing dengue, but also for the Zika virus [4].

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