

Risk-assessment of Mosquito-borne Diseases in African Cities

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Abstract

Mosquito-borne diseases such as malaria, dengue, and yellow fever have been spreading across African cities, placing more than 126 million residents at risk of large-scale outbreaks. Poor housing quality is a key driver of mosquito-borne diseases, yet the role of the urban built environment in shaping the transmission dynamics of these diseases remains understudied. Therefore, we assess the risk-factors from the built environment and how they are related to vector-borne diseases. To do so, we extract these risk-factors from high-resolution remote sensing imagery with deep learning to identify high-risk areas and to inform targeted intervention strategies. Here, we present initial results on mapping some of the high risk-factors from drone imagery. Our findings demonstrate the ability to capture fine-grained urban details, such as roof materials and small water-holding containers, which are critical indicators of vector habitats.

Keywords: Vector-borne diseases, remote sensing, deep learning

1 Introduction

Mosquito-borne diseases are transmitted by the bite of mosquitoes. Malaria is such a disease spread through infected female *Anopheles* mosquitoes. It ranks among the world’s most serious public health problems and is a leading cause of mortality and disease in many developing countries. Therefore, it is crucial to improve the prevention, control, and surveillance measures of malaria, particularly in sub-Saharan Africa [Venkatesan, 2024, WHO, 2023]. Mosquito-borne diseases, which also include dengue, chikungunya and Zika, pose a major public health problem and a growing concern in urban areas of endemic countries. Transmitted by *Aedes* mosquitoes, these viruses are responsible for major outbreaks and are spreading into new regions, driven by rapid urbanization, climate change, altered vector ecology, and increasing insecticide resistance [Weetman et al., 2018, WHO, 2022, Ramphal et al., 2024, Mweya et al., 2016, Situma et al., 2024]. Urban environments with informal settlements are particularly vulnerable, as *Aedes* mosquitoes preferentially exploit man-made water containers and other artificial habitats, making densely populated cities especially high-risk for transmission [Mustafa et al., 2024, Vairo et al., 2016].

Using deep learning, we can extract risk factors from remote sensing data that indicate where these diseases are transmitted and where mosquitoes breed and increase their population (e.g., water-filled tires on rooftops), particularly those contributing to the above-mentioned diseases. In particular, we study low-quality housing and breeding sites of *Aedes* mosquitoes. Low-quality housing built of natural materials, for example, having a thatched roof of grass or palm, is associated with an increased risk of malaria infection [Dlamini et al., 2017]. Substandard housing has more mosquito entry points and most malaria transmissions in sub-Saharan Africa occur inside dwellings while the inhabitants sleep [Tusting et al., 2020, 2017, Jatta et al., 2018, Tusting et al., 2019]. Houses with metal roofs are hotter in the daytime than houses with thatched roofs, which may reduce mosquito survival and inhibit parasite development within the mosquito. Thus, the proliferation of modern construction materials in sub-Saharan Africa may have contributed decisively to the reduction of malaria cases [Tusting et al., 2019]. *Anopheles* mosquitoes breed in sunlit, larger water bodies, while *Aedes* mosquitoes prefer small artificial containers [Venkatesan, 2024]. In our recent pilot study in Dar es Salaam, we found that there are more *Aedes* mosquitoes than *Anopheles*. Therefore, we are interested in smaller containers that are breeding sites for the *Aedes* mosquitoes.

In the following, we present our initial results for (1) Roof material classification in Nacala, Mozambique [Guthula et al., 2025] and (2) Larval breeding site mapping in Dar es Salaam, Tanzania.

2 Data and Methods

Roof material data. We gathered drone imagery of the Nacala region in Mozambique. We annotated all buildings on drone imagery along with the roof

material of that building. We distinguished five main types of roof materials in Nacala, namely metal sheet, thatch, asbestos, concrete, and no-roof, and delineated 9776, 6428, 566, 174, and 1010 roofs of these classes. The region is dominated by metal sheets and thatch roofs. Fig. 1 shows buildings with different roof materials with building characteristics. The dataset is split into training, validation, and test using stratified sampling. The data can be downloaded from <https://mosquito-risk.github.io/Nacala>.

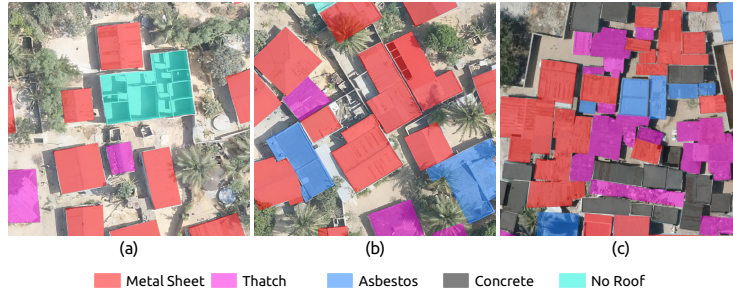


Figure 1: Examples of different spatial distribution characteristics of buildings in our dataset. (a) well-separated buildings (b) Buildings are close but still separable using segmentation methods. (c) Ambiguous boundaries that make individual buildings difficult to segment

Breeding sites. We gathered drone imagery of the Dar es Salaam region in Tanzania, across all 20 sampled locations, with an area of 27.27 km². A cumulative area of 4.60 km² within 20 sampled locations was annotated manually. The proxy annotations for breeding sites are tires, water tanks, and buckets or jerry cans. Fig. 2 shows buildings with different roof materials with building characteristics. The labeled drone imagery was split into training, validation, and test set.

Methods. We trained a U-Net [Ronneberger et al., 2015] kind of model with a ResNet34 [He et al., 2016] backbone on both datasets. The final weight configuration and hyperparameters for each model were selected based on the highest IoU score on the validation dataset.

3 Results and Discussion

Table 1 and Table 2 present the results for the two applications. The mean and standard deviation of five trials are reported in both tables. The main challenge in both tasks is class imbalance: the roof material dataset contains fewer samples of concrete roofs and no-roof cases, while the breeding sites dataset includes very few small objects such as buckets and tires. Another issue in the



Figure 2: Annotations on drone imagery on the left side of the image, with an image captured from the ground at the highlighted location on the image

Class	IoU (Mean $\pm$ SD)
Metal Sheet	0.819 ± 0.012
Thatch	0.880 ± 0.004
Asbestos	0.514 ± 0.025
Concrete	0.306 ± 0.091
No Roof	0.650 ± 0.029
Macro Average	0.634 ± 0.032

Table 1: Results on the roof material test set

Class	IoU (Mean $\pm$ SD)
Buckets	0.309 ± 0.012
Tires	0.374 ± 0.193
Water Tanks	0.677 ± 0.013
Macro Average	0.453 ± 0.073

Table 2: Results on the test set for detecting breeding sites

roof material dataset is object separation—accurately segmenting individual objects and classifying their roof materials is crucial. We have explored different approaches to address these challenges; see [Guthula et al., 2025] for details. The roof material dataset from Mozambique is publicly accessible¹, the larval habitat datasets can be provided upon request.

4 Conclusions

We collected high-resolution drone imagery from two African cities and trained a U-Net model to monitor key risk factors, roof materials that indicate housing quality and containers that serve as breeding sites for *Aedes* mosquitoes. In future work, we plan to identify additional risk factors from both drone and satellite imagery and integrate these results with ground data.

¹<https://mosquito-risk.github.io/Nacala/>

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