Unmanned Aerial Vehicles for Mosquito-Borne Viral Diseases

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Unmanned aerial vehicle (UAV) technology has developed in recent years; its applications avoid many of the limitations associated with satellite data, such as long repetition times, cloud contamination, low spatial resolution, and lack of homogeneity in camera angle or shooting time.

Aedes aegypti UAV risk model FAMD PLS

1. Introduction

Unmanned aerial vehicle (UAV) technology has developed in recent years; its applications avoid many of the limitations associated with satellite data, such as long repetition times, cloud contamination, low spatial resolution, and lack of homogeneity in camera angle or shooting time [1]. It also offers the possibility of collecting detailed spatial information in real time at a relatively low cost [2][3]. They carry out highly detailed imaging work with essential high spatial resolution, spectral, and temporal characteristics [4][5][6][7]. Likewise, unmanned aerial vehicles (UAVs) are developing technology for remote-sensing applications based on passive sensors, such as RGB, multispectral, hyperspectral, thermal cameras, and active sensors, such as LiDAR or RADAR [8][9].

The UAVs can provide precise spatial and temporal data to understand the links between disease transmission and environmental factors [2][3][10]. Moreover, it is a flexible and low-cost solution for mapping mosquito breeding sites and the operational dissemination of strategies in mosquito-elimination campaigns. It can be used in communication materials to demonstrate the specific risk conditions for a given area [5][11]. Through aerial surveillance, possible mosquito breeding sites could be identified in domestic areas inaccessible to traditional ground surveillance, which allows them to be proposed as a useful and complementary tool in surveillance programs and mosquito control [12]. Likewise, it can help operators of vector-control actions to optimize treatments by accurately identifying and mapping the coverage of breeding sites by using standard and multispectral images [13][14]. Orthomosaics provide vital information for other public health planning activities [11].

The physical landscape characteristics influence the distribution of adult female mosquitoes [15] as interrelated socioeconomic, environmental, and behavioral factors can explain the presence and abundance of *Aedes aegypti* [16]. Anthropogenic environmental changes can create an overabundance of resources responsible for sustaining vector mosquito species' invasion, spread, and colonization of urban areas [17]. Vegetation cover is an important environmental factor that allows optimal conditions for mosquito life-cycle development [18][19]. The organization of the backyard, knowledge about vector biology, and cleaning containers are identified as the main topics for future prevention strategies for the transmission of dengue in the local and national context [20].

New technologies for mosquito surveillance are growing; drones and specialized cartography, machine learning, deep learning, big data, and citizen science can be added as tools for better understanding the mosquito population dynamics and determining the areas at risk to better conditions for spreading mosquito populations [21]. Predictive models can be used for decision making in preventing various arboviruses transmitted by *Ae. aegypti* in endemic urban and semiurban areas. Building a model that determines the power and association of different variables is a necessary challenge because the *Ae. aegypti* mosquito exists in complex environments with complex dynamics, where numerous factors intervene in different dimensions, and each one can have a different role of lesser or greater importance. However, it does not stop influencing the response of the vector to the differences in the landscape.

In this research, by UAV cartography, field surveillance, and algorithm development, researchers design a risk index to determine which houses have the environmental, demographic, and socioeconomic characteristics to be classified as “aedic” houses for immature and adult *Ae. aegypti* mosquitoes in Tapachula, Chiapas, a city on the Mexican southern border. This proposed methodology can adapt the model to the different regions of our country, and this flexibility is allowed mainly by the availability of real-time information provided by UAV, one of its most important contributions.

Nonetheless, for the best performance of the UAV, it is necessary to consider the meteorological conditions and know the flight area [22][23] and the terrain’s characteristics, such as tall trees and telecommunication antennae, to avoid electromagnetic interference [22]. As a user of UAVs, the national regulations must be observed [24]. Moreover, it should be considered that one of the factors for UAV flight coverage depends on the battery time [3][23]. Indeed, before the flights, the field teams should visit and talk with the health authorities, principal neighborhood actors, and community leaders, who are necessary for developing these new tools [25]. The costs of this technology must be taken into account and considered as open-source software for affordable technology. A multidisciplinary team is also required to address the entire strategy.

2. Unmanned Aerial Vehicles for Mosquito-Borne Viral Diseases

Studies on UAV applications in health are scarce. They addressed simulations on using drones for out-of-hospital care in cardiac arrest emergencies, identification of people after accidents, transport of blood samples, and improvement of surgical procedures in war zones [26]. UAVs can transport medical supplies, specimens, biological materials, and vaccines to hard-to-reach areas at a reduced travel time. Moreover, the research on the use of drones in health is almost limited to simulation scenarios [26][27].

In mosquito-surveillance and control programs, UAVs have been designed to control mosquitos by spraying larvicides, dropping larvicide tablets, spreading larvicide granules, the application of adulticides in ultra-low volume, sampling in bodies of water, and surveillance of adult mosquitoes [28][29]. Likewise, drones can help operators of vector-control actions to optimize treatments by accurately identifying and mapping the coverage of breeding sites by using standard and multispectral images [14] and as tools for the release of sterile mosquitoes [30][31].

Indeed, three years ago, different studies were conducted to evaluate the use of UAVs to identify the larval breeding sites of different mosquito species. In Peru, multispectral mapping was used with random forest analysis to identify *Anopheles darling* larval breeding sites [32]. In Brazil, it was used to detect *Ae. aegypti* breeding sites [33]. In Mexico, the first study evaluating UAVs was carried out to identify *Ae. aegypti* breeding sites [12].

In studies of spatiotemporal distribution models of *Ae. aegypti* vectors, the limited availability of high-resolution data for physical variables stands out as part of the inconsistencies in the number and influencing factors [34]. Few studies comprehensively highlight the interaction between environmental, socioeconomic, meteorological, and topographical systems [34]. Maximum entropy species-distribution models have been used, with human population density, distance to vegetation, water channels [35], population density, and poverty [36] being the main predictor variables of the vector suitability of a given area.

There are few works reported in the literature about the use of machine learning (ML) and nonparametric techniques for mosquito surveillance. In [37], authors used three ML models (nonlinear discriminant analysis, random forest, and generalized linear models) to analyze the environmental suitability of three indigenous mosquito species in the Netherlands: *Culiseta annulata*, *Anopheles claviger*, and *Ochlerotatus punctor*, where the response variable is mosquito abundance sampled at 778 locations by using CO –baited mosquito magnet traps. As covariates, they used environmental variables obtained from satellite images and meteorological data. The best results were achieved with random forests, and they showed the most discriminative variables for each species. In [38], the authors used classification methods based on –nearest neighbor, support vector machines, neural networks, and random forest to predict mosquito abundance in 90 sampling sites from Charlotte, NC, USA. The data consisted of mosquito samples collected with gravid traps and socioeconomic and landscape factors. The dependent variable to predict mosquito abundance was binarized as low (0) and high (1) according to the median value, and the independent variables or predictors were divided into seven socioeconomic variables and seven landscape variables obtained from remote-sensing images. Two versions of the input variables were used, one dichotomized into binary values according to the median of each variable, and one with the raw continuous values scaled. The best performance was achieved with the –nearest neighbor algorithm in both cases; however, there are no further details about the distance metric used in the binary input variables case, because, except for random forest, all classification methods use Euclidean distance as the default option, even when a nonlinear kernel or activation function is used; i.e., they are originally formulated for continuous input variables. In [39], 1066 females adult *Ae. aegypti* were collected by using battery-powered Prokopack aspirators from 128 indoor and outdoor houses in northeastern Thailand to map and predict the female adult *Ae. aegypti* abundance. They used five popular supervised learning models (logistic regression, support vector machine, –nearest neighbor, artificial neural networks, and random forest) based on socioeconomic, climate change, dengue knowledge, attitude, and practices (KAP), and/or landscape factors to predict the abundance considering only two classes (high and low). In this research, the random forest method had the highest prediction model accuracy, and the research demonstrated that climate change, KAP, and landscape factors were more important than socioeconomic factors in explaining mosquito abundance. Similar to [38], it is not clear how the mixed input data (categorical and continuous) are managed, because the classification models they used (except random forest) cannot naturally handle mixed-type data. This may be the reason why random forest showed the best results.

Those approaches are interesting in terms of prediction, and the use of ML models provides flexibility because most of them are nonparametric and do not assume a priori any probability distribution of data. However, for researchers it is very important to gain some insight into the local characteristics of the area of study, which makes it more prone to mosquito-borne diseases. A study of the importance of the variables can be done based on the parameters of the models [37][39], when it is possible, correlation analysis, or by a specific hypothesis tested on the models [38], based, for example, on manually adding or excluding individual variables or sets of variables [39]. All those approaches must be carried out carefully when researchers' variables are mixed-type data, particularly for ML models based on Euclidean distance between observations. For this reason, in the approach researchers pay special attention to obtaining an adequate distance metric for mixed-type data, which allows to obtain an index representing the local characteristics of houses that are related in some way to dengue disease.

Despite the scientific evidence available, the objectives of each previous study—to analyze the available entomological, epidemiological, and environmental data in defined study areas and to consider different types of variables—have been limited in terms of technology, resolution, and frequency of images available. Having high-resolution, real-time, and more accessible images taken by UAVs dictates the need to evaluate their use with predictive power within the prevention and control of vector-borne diseases. Prior knowledge is a good foundation, but current technology allows to analyze the dynamics of different changes at different spatial scales, such as overpopulation, urbanization, and climate change.

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