American Journal of Entomology
2021; 5(4): 92-109
http://www.sciencepublishinggroup.com/j/aje
doi: 10.11648/j.aje.20210504.11
ISSN: 2640-0529 (Print); ISSN: 2640-0537 (Online)

Geospatial Artificial Intelligence Infused into a Smartphone Drone Application for Implementing 'Seek and Destroy' in Uganda

Benjamin George Jacob[1, *], Denis Loum[2], Martha Kaddumukasa[3], Joseph Kamgno[4], Hugues Nana Djeunga[4], André Domche[4], Philip Nwane[5], Joseph Mwangangi[6], Santiago Hernandez Bojorge[1], Jeegan Parikh[1], Jesse Casanova[7], Ricardo Izureta[1], Edwin Micheal[1], Thomas Mason[1], Alfred Mubangizi[8]

[1]College of Public Health, University of South Florida, Tampa, USA

[2]Nwoya District Local Government, Nwoya, Uganda

[3]Department of Parasitology and Entomology, Makerere University, Kampala, Uganda

[4]The Center for Research on Filariasis and other Tropical Diseases, Yaounde, Cameroon

[5]The University of Yaoundé I, Yaounde Cameroon

[6]Center for Geographic Medicine Research, Coast, Kilifi, Kenya

[7]USF Health International University of South Florida, Tampa, USA

[8]Uganda Ministry of Health, Kampala, Uganda

Email address:

bjacob1@usf.edu (B. G. Jacob), loumdenis2@gmail.com (D. Loum), mkaddumukasa@gmail.com (M. Kaddumukasa), kamgno@crfilmt.org (J. Kamgno), nanadjeunga@crfilmt.org (H. N. Djeunga), domche_andre@yahoo.fr (A. Douche), philippenwane16@gmail.com (P. Nwane), JMwangangi@kemri-wellcome.org (J. Mwangangi), santiagohern@usf.edu (S. H. Bojorge), jeeganparikh@usf.edu (J. Parikh), jcasanov@usf.edu (J. Casanova), ricardoi@usf.edu (R. Izureta), emichael443@usf.edu (E. Micheal), QualtricsMailer@usf.edu (T. Mason), alfmbngz@yahoo.com (A. Mubangizi)

[*]Corresponding author

To cite this article:

Benjamin George Jacob, Denis Loum, Martha Kaddumukasa, Joseph Kamgno, Hugues Nana Djeunga, André Domche, Philip Nwane, Joseph Mwangangi, Santiago Hernandez Bojorge, Jeegan Parikh, Jesse Casanova, Ricardo Izureta, Edwin Micheal, Thomas Mason, Alfred Mubangizi. Geospatial Artificial Intelligence Infused into a Smartphone Drone Application for Implementing 'Seek and Destroy' in Uganda. *American Journal of Entomology*. Vol. 5, No. 4, 2021, pp. 92-109. doi: 10.11648/j.aje.20210504.11

Received: August 10, 2021; **Accepted**: September 28, 2021; **Published**: MM DD, 2021

Abstract: This study provided important insights into new, real time, control measures at reducing larval, vector density [Macro Seek and Destroy (S&D) and blood parasite level [Micro S&D] in a malaria treated and suspected intervened population. Initially, this study employed a low-cost (< $1000) drone (DJI Phantom) for eco-geographically locating, water bodies including natural water bodies, irrigated rice paddies, cultivated swamps, ditches, ponds, and other geolocations, which are among the common breeding sites for *Anopheles* mosquitoes in Gulu district of Northern Uganda. Our hypothesis was that by integrating real time, scaled up, sentinel site, spectral signature, unmanned aerial vehicle (UAV) or drone imagery with satellite data using geospatial artificial intelligence [geo-AI] infused into an iOS application (app), a local, vector control officer could retrieve a ranked list of visually similar, breeding site, aquatic foci of *An.gambiae s.l. arabiensis s.s. fuentsus s.s.* mosquitoes, and their respective district-level, capture point, GPS indexed, centroid coordinates. We real time retrieved (hence, no lag time between seasonal, aquatic, *Anopheles*, larval habitat, mapping and treatment of foci) each georeferenced sentinel site signature which was subsequently archived in the drone dashboard spectral library using the smartphone app. Each georeferenced, UAV sensed, capture point was inspected using a mobile field team (i.e., trained local village residents led by a vector control officer) on the same day the habitats were geo-AI signature mapped, spatially forecasted and treated. A second hypothesis was that a real time, environmentally friendly, habitat alteration [i.e., Macro S&D] could reduce vector larval habitat density and blood parasite levels in treated and not suspected malaria patients at an entomological intervention site. A third hypothesis was: timely malaria diagnosis and treatment [Micro S&D] is associated with low population parasitemia and lower malaria incidences. In 31 days post-Macro S&D intervention, there was zero vector density, indoor, adult, female, *Anopheles* count as ascertained by pyrethrum spray catch at the intervention site. After a mean average of 62 days, blood parasite levels revealed a mean 0 count in timely diagnosed suspected and treated malaria patients. Implementing a real time Macro and Micro S&D intervention tool along with other existing tools [insecticide-treated mosquito nets (ITNs) and indoor residual spraying of insecticides (IRS)] in an entomological district-level intervention site can lower seasonal malaria prevalence either through timely modification of aquatic, *Anopheles*, larval habitats or through precisely targeted larvicide interventions.

Keywords: Drone, Seek and Destroy, ArcGIS, Artificial Intelligence iOS, *Anopheles*

1. Introduction

Current efforts use Unmanned Aerial Vehicles (UAVs, also called drones) to map habitats of malaria, mosquito, *Anopheles* [1, 2] but are unable to scale broadly from a sentinel site, [e.g., seasonal, hyperproductive, capture point, larval, aquatic foci] to complete land footage across any malarious, district-level, suitable region of interest [e.g., fresh or salt-water marshes, mangrove swamps, furrows, rice fields, grassy ditches, the edges of streams and rivers, temporary rain pools, pit latrines etc.]. The scalability process would be tremendously time-consuming and expensive, especially considering that a typical drone can only fly for approximately 30 minutes, covering approximately three acres before requiring recharging. Overlapping photos collected of potential, georeferenced, sentinel site, *Anopheles*, larval habitat, capture points [e.g., deteriorating infrastructure such as broken water pipes, poorly maintained drains, culverts, market gardens/urban agricultural sites, pools at construction sites, tire tracks on unpaved roads, low lying areas that are liable to flooding, hydrants, catch pits etc.] during a drone flight can be used for identifying larval habitats during the dry season, however, processing the imagery takes two to three hours. Real time larval control is of paramount importance in the reduction of malaria vector abundance and subsequent disease transmission reduction [3]. Drone imagery alone is not ideal during rains or clear sky's (drones are flown under clouds). Real time, sentinel site, UAV mapping, forecasting, and treating only dry, seasonal, breeding site, aquatic, larval habitats of *Anopheles* would not lower district-level malaria prevalence. Since unknown, sentinel site, capture point, *Anopheles*, breeding site, habitat geolocations cannot be mapped or treated during pre-rain and rainy seasons; there currently is no ability to implement year-round control strategies [i.e., Micro and Macro S&D] as part of a real time Integrated Vector Management (IVM) program in a malarious district. Integrated vector management (IVM) is a rational decision-making process that encourages optimal use of resources for efficient, cost-effective and sustainable vector control [4].

To date most examples of integrated control targeting malaria have been unanticipated consequences of vector control, rather than planned strategies that aim to maximize the efficacy and take the complex seasonal ecological and biological interactions between land cover and development of seasonal, aquatic, larval habitat, breeding sites of *Anopheles.* Conventional UAV habitat monitoring methods are time-consuming and labor-intensive, necessitating new techniques to provide faster scaling up of capture point measurements for detection of *Anopheles* larvae and the collection of epidemiological, eco-hydrogeological, topographical, and biogeographical capture point, spectral temporal [henceforth spectrotemporal], land use land cover [LULC] change data [e.g., from pre-rain, pre-flooded, rice paddies to dry seasonal intermittently shade canopied, post harvested, mature tillers]. Doing so would allow for real time sampling intensity mapping, sentinel site, signature forecasting and treating, georeferenceable, aquatic, *Anopheles,* larval, breeding site, aquatic foci throughout the seasons.

Combining artificial intelligence (AI) machine learning classifiers and interpolative, ArcGIS [geo-AI] in an interactive, dashboard configurable, web-friendly, smartphone application (app) can aid in optimally scaling up sentinel site capture points for predictively mapping unknown, district-level, *Anopheles*, larval habitat, seasonal, occurrence, abundance and distribution. By employing real time, UAV retrieved, capture point, sentinel site, wavelength, reflectance datasets of seasonal, imaged, LULC classified, *Anopheles* larval habitat characteristics [e.g., water situation (turbid or clean, stagnant or running), substrate type, (e.g., moist or dry) site type (man-made or natural), sunlight situation, site situation (transient or permanent, with or without vegetation) etc.] a georefereceable Red Green and Blue (RGB), signature may be generated employing geo-AI technologies infused into an iOS app. Spectral signature is the variation of reflectance or emittance of an object with respect to wavelengths (i.e., reflectance/emittance as a function of wavelength) [5] which may be interpolated in ArcGIS to geolocate unknown objects or materials of an object [e.g., sentinel site, capture point, *Anopheles*, larval habitat breeding site, seasonal, aquatic foci]. In the mathematical field of numerical analysis, interpolation is a type of estimation, a method of constructing new data points based on the range of a discrete set of known data points [6]. This protocol has been employed to identify the aquatic sources for Black Fly larvae and pupae in West and East Africa (Cameroon and Uganda, respectively) [7] as well as the potential geolocations for immature (larval) habitat sources of *Chrysop* species the vector of *Loa Loa* and the source locations for container species of mosquito, *Aedes aegypti* and *Ae. albopictus* in a county mosquito abatement in Florida USA [8]. Since these model systems are built on spectral signatures of habitats and employ a real time IVM system of geolocating those areas where seasonal, vector arthropod, larval habitat population is the most concentrated, immobile and accessible, the method has several ramifications regarding its biological utility as a real time tool for surveillance, monitoring and the direction and implementation of control applications by prioritization of nuisance. The sites in question could be specifically identifiable by georeferenced capture points and subsequently scaled up and treated via real time, dashboard technology, or by standard mosquito operational tactics depending on the site's landscape. In addition, this system could also provide the specific geolocation for adult emergence forecasting the where, when, and time to initiate an adult control operation. Thus, individuals would be treated before they disperse, and when the adult population is highly concentrated pre-dispersal.

Drone dashboard video data has the ability to map seasonal, georeferenced, LULC classified, capture point, aquatic, *Anopheles,* larval habitat, RGB indexed, spectral signature, sentinel sites in real time. Machine learning and geo-AI can subsequently train dashboard tools to solve complex spatial problems such as scaling up a georeferenced, capture point, LULC, classified site for identifying district-level, unknown, larval habitats using UAV sensed, *Anopheles,* sentinel site, seasonally indexed, capture point, RGB signatures, and high-resolution satellite data.

Here we assumed geo-AI technologies could provide important advantages for seasonal, UAV capture point, signature, entomological, prognosticative modeling unknown district-level, *Anopheles,* larval habitat geolocations by incorporating large, LULC classified, empirical datasets of real time, archived, aquatic, seasonal, sentinel site, RGB signatures in a web-configurable smartphone app. We assumed that by employing a variety of formats; computational efficiency; flexibility in algorithms and workflows to accommodate relevant characteristics of environmental processes including spatial nonstationarity; and scalability to model previously, unknown, seasonal *Anopheles* breeding sites across different, district-level, geographic area we would be able to implement a real time IVM. Our assumption was that geo-AI technologies infused into an intercative smartphone app could produce effective machine learning models by incorporating spatial data and geolocation-infused algorithms for finding, unknown, district-level, natural sites or clusters of *Anopheles* based on spatial distribution of stochastically interpolated, RGB indexed, seasonal aquatic, larval habitat, capture point, signatures and then treat them. We employed sentinel site signature reflectance wavelength similarities [vegetation, turbid water pixels] for seasonally classifying satellite sensed, sub-meter resolution, capture point LULC data in an iOS app for improving the scalability of a spectrotemporal district-level, UAV, vulnerability model. Consistent with that, the major innovation in this project is the potential scalability afforded through a combination of the geo-AI object-based object detection algorithms in an interactive, configurable, smartphone app for real time, video analog and satellite mapping grid-stratifiable, geolocations of unknown district-level, georeferenced, aquatic, *Anopheles,* larval habitats from a single, RGB indexed, capture point, seasonal signature, and subsequently treating the interpolated, field verified individual, breeding sites or clusters using real time IVM tools [e.g., web-configurable smartphone apps for Macro S&D targeted drone larviciding].

Advances in computer vision have made it possible to get credible intelligence from UAV and satellite imagery using geo-AI techniques such as Deep Learning in ArcGIS. For example, ArcGIS Pro allows the usage of machine learning classification [e.g. Random Forest (RF)] classification algorithm] methods to classify real time, sentinel site, vector arthropod, seasonal archived, UAV and/or remotely-sensed, RGB, signature imagery. Random Forest ensemble models are made of many decision trees using bootstrapping, random subsets of features, and average voting to make predictions [9]. Here the improved ability of multispectral sensors and the statistical and machine learning computational geoprocessing tools in ArcGIS Pro provided an essential real time, sensing data resource for optimizing spatial data visualization of UAV retrievable, seasonal, quantitative, thematic information, [e.g., marshy land cover of a georeferenced, semi-permanent, sentinel site, aquatic, *An. funestus* larval habitat,) employing a web-configurable, interactive, smartphone app. Subsequently we scaled-up the RGB indexed databases of seasonal, sentinel site signatures and the capture point's grid-stratifiable, LULC classifiable, habitat objects using geo-AI intelligence in the app for mapping unknown, *Anopheles,* district-level, larval, breeding sites for implementing real time IVM. For example, one of the objectives of this research was to construct a real time UAV system where a query video is infused into an iOS for retrieval of a ranked list of visually similar, classified, land cover, grid-stratified, *Anopheles* habitats by differentially corrected GPS coordinates employing the interactive dashboard app. A vector arthropod Differential Global Positioning System (DGPS) [10] is an enhancement to the Global Positioning System (GPS) which provides improved habitat geolocation accuracy, in the range of operations of each system, from the 15-metre (49 ft) nominal GPS accuracy to about 1–3 centimeters (0.39–1.18 in) [11]. The sensitivity and specificity of the video analog signals at identifying and scaling up multiple, land cover, seasonal, grid-stratifiable, LULC classifiable, aquatic, *Anopheles,* larval habitat, RGB sentinel site, signatures was field validated. We assumed that the iOS app would yield data approximation, peak sharpening, non-linear smoothing, and all manner of hybrid schemes in a principled way by a deliberate choice of different geo-AI algorithms for optimally seasonal mapping, unknown, breeding site, district-level, *Anopheles,* aquatic, foci based on a scaled-up, UAV sensed, real time, retrieved, RGB sentinel site, satellite signature within an interactive smartphone app framework.

The field of machine learning is broad, deep, and constantly evolving. ArcGIS is an open, interoperable platform that allows the integration of complementary methods and techniques in several ways: through the ArcGIS API for Python, the ArcPy site package for Python, and the R-ArcGIS Bridge. This integration empowers ArcGIS users to solve complex problems by combining powerful built-in tools with any machine learning package required—from scikit-learn and TensorFlow in Python to caret in R to IBM Watson and Microsoft AI—while benefiting from spatial validation, geoenrichment, and visualization of results in ArcGIS [12]. We assumed that the combination of these complementary packages and technologies within a real time, web configurable, iOS, interactive platform, would allow for non-heuristically optimizing signature feature identification and seasonal, LULC pattern recognition of georeferenced, sentinel site, real time, UAV imaged, *Anopheles,* larval habitat, aquatic foci. We further assumed that a vulnerability-oriented, district-level, scaled-up, georeferenced, capture point, RGB indexed, stochastically interpolated, geo-AI constructed, sentinel site, signature, seasonal, grid-stratified, LULC map might be constructed in the smartphone app for implementing real time IVM strategies [i.e., Maco and Micro S& D] for treating previously unknown, district-level, individual, or clusters (i.e., “hot spots”) of breeding site, *Anopheles,* larval habitat, aquatic foci.

Here we constructed, real time, deep learning, convolution neural network,[CNN], signature models which were integrated with ArcGIS Pro employing real time, sentinel site, object detection algorithms in the smartphone app for seasonal, georeferenceable, LULC mapping specific, *Anopheles,* larval habitat, capture point, attribute features [e.g., levels of intermittent, canopy cover of a sentinel site, commercial grassy, roadside ditch]. We did so to optimize seasonal, sentinel site, UAV sensed, RGB signature, image classifications of unknown, seasonal, district-level, *Anopheline,* larval habitat, breeding site, aquatic foci in the dashboard, configurable, interactive iOS app for implementing district-level, real time IVM control strategies [e.g., targeted, drone larviciding of a georeferenced, scaled-up, field verified, post-flooded, household, vehicle rut or domestic animal hoof print, breeding site aquatic foci using high-resolution satellite data [i.e., WorldView (Wv)-2, 46, centimeter resolution, LULC data]. CNN is an algorithm for image classification and typically comprises of convolution layers, activation function layers, pooling (primarily max_pooling) layers to reduce dimensionality without losing a lot of LULC attribute features [13]. Convolutional neural networks are composed of multiple layers of artificial neurons, which are mathematical functions that calculate the weighted sum of multiple inputs and predicted outputs using an activation value [14]. Based on a real time, stochastically interpolated, spectrotemporal dependent, UAV sensed, sentinel site, georeferenceable, satellite signature, in an activation map, we were confident that the classification layer in an interactive, web-friendly, configurable, iOS app could output a set of confidence scores which could be specified based on how likely the image belongs to a "class." [e.g., grid-stratified, LULC classified, cover where *Anopheles* mosquitoes breed such as ground pools, small streams, freshwater marshes, forest pools, paddy fields, etc]. We also assumed that a wayward, sentinel site, UAV imaged, georeferenced, *Anopheles,* larval habitat signature, interpolation, forecast, vulnerability, LULC map might be created in a interactive smartphone app which could allow real time spot targeted treatment [Macro S & D] of a field verified, district-level, seasonal, aquatic, larval habitat, *Anopheles* foci from a scaled up, capture point, using high resolution satellite data.

Our approach is based on a region-based convolutional neural network (R-CNN) embedded in an iOS interactive app. Region Based Convolutional Neural Networks (R-CNN) are a family of machine learning models for computer vision and specifically object detection. We successfully merged a region proposal network (RPN) and Fast R-CNN [i.e., a machine learning classifier] within a dashboard, smartphone, interactive app to build on archived, datasets of real time, UAV sensed, georeferenced, capture point, seasonal, aquatic, *Anopheles,* larval habitat, RGB sentinel site, signatures by classifying grid-stratifiable, LULC capture points (e.g., edges of streams and water puddles on drying streambeds, agro-pastureland ecosystem, community tap foci etc.) Mask R-CNN [14] and the architecture of Faster R-CNN [15] were employed for identifying georeferenceable, seasonal, aquatic, *Anopheles,* larval habitat, sentinel site, RGB signatures which in this experiment were developed in two stages in the interactive, smartphone app. The first stage consisted of two networks, backbone (ResNet, VGG, Inception, etc.) and region proposal network [RPN]. These networks ran once per, sentinel site, UAV sampled, capture point in the app, which subsequently rendered a set of region proposals [i.e., georferenceable district-level, geolocations in a feature, signature, interpolated, probability map which contained a forecasted, breeding site, larval habitat, positive for *Anopheles* larvae/pupae and its associated land cover]. In the second stage, the network in the app predicted bounding boxes and object class for each of the proposed regions obtained in stage1. Each proposed region was of different size, whereas fully connected layers in the network required fixed size vector to make robust predictions [e.g., exact DGPS centroid coordinates of the capture point, *Anopheles,* breeding site, aquatic foci]. The size of these proposed regions was fixed in the app by employing the Region of Interest [RoI] pool method. RoI pooling solved the problem of fixed image size requirement for sentinel site, seasonal, object detection networking. Here, the entire image fed a CNN model to detect RoI on the feature, *Anopheles,* larval habitat, signature LULC maps in the app.

We fused deep convolutional networks into a single network in the interactive drone dashboard app. In so doing, the app was able to scale-up convolutional features of the georeferenced, UAV sensed, capture point, aquatic, *Anopheles*, larval habitat, RGB, indexed, grid-stratified, LULC classified, sentinel site signatures while real time communicating with a unified real time network. Among the data exported included georeferenced DGPS geolocations of unknown, seasonal, scaled-up, district-level, breeding site, aquatic foci employing high resolution, gridded, satellite data [i.e., visible and near-infrared (NIR) bands from Wv-2 data] of an entomological malarious intervention site, Gulu District in Northern Uganda. This data was stratified based on an archived, trained, remotely retrieved, capture point database of multivariate sampled, RGB indexed, spectrotemporal, sentinel site signatures conceived in a real time ArcGIS. The RPN in the app utilized a fully convolutional network that simultaneously identified object bounds and objectiveness scores (i.e., 1=breeding site, 0= no breeding site) (e.g., a georeferenced *An. funestus* larval habitat in a cultivated papyrus swampland,) for every single, real time, UAV sensed, grid-stratifiable, land cover classified, image frame archived in the iOS app platform. The RPN was subsequently trained end-to-end to generate high-quality region proposals [i.e., georeferenceable, geolocations of unknown, district-level, *Anopheles* habitat breeding sites] in the interactive smart phone app.

Further, a Machine learning Grid, Network portal was constructed in the iOS app platform for geoprocessing fused, grid-stratifiable seasonal, LULC classifiable, surface retrievable, RGB indexable, sentinel site, aquatic, *Anopheles,* larval habitat, reflectance wavelength, spectral data (e.g., capture point, drone imaged, turbid water, surface reflectance). We imported multiple, sentinel site, georeferenced coordinates into the web configurable, real time, interactive dashboard. Machine learning algorithms and video analog signature, sentinel site, real time, model outputs retrieved from the app (i.e., "training data') was subsequently employed to generate prognostications of unknown, district-level, capture point, *Anopheles,* larval habitat, aquatic foci for implementing a real time IVM [Macro/Micro S&D] [e.g., drone larviciding a field verified, deep learning/CNN, seasonal, forecasted, agro-pastureland *Anopheline* breeding site].

Here an R-CNN mask was applied to the real time, seasonal, forecasted, grid-stratified, LULC, UAV sampled, surface sample, scaled-up, RGB indexed signatures in the dashboard app which included the video analog, sentinel site, georeferenced, aquatic, *Anopheline,* larval habitat, priori information extracted from the capture points. Our hypothesis was that geo-AI intelligence powered by machine learning automation in an operational, configurable dashboard, web app could aid in optimizing seasonal, sentinel site, UAV forecast, vulnerability, LULC mapping district-level, georeferenceable, aquatic, *Anopheles,* larval habitat, breeding sites using stochastically interpolatable, capture point RGB, signatures archived in an ArcGIS, neural network spectral library. Our second hypothesis was that real time, geo-AI machine and deep learning algorithms and remote sensing object detection algorithms embedded in an interactive smartphone dashboard app could cost-effectively and precisely implement a real time, district-level, IVM program [i.e., Macro and Micro S&D].

Hence, our objectives in this research were to 1). Design, deploy and validate a new real time tool using geo-AI algorithms operating on UAV videos in conjunction with an interactive dashboard smartphone app for real-time, forecast, sentinel site, signature, grid-stratifiable LULC, vulnerability mapping seasonal, *Anopheles,* larval habitat, breeding site, aquatic foci. 2). Test the scalability of the habitat signatures in the iOS app for detecting district-level, unknown georeferenceable habitats from drone video across seasons using an interpolated, RGB indexed, sentinel site, capture point, spectral signature 3). Implement an environmentally friendly intervention [i.e., Macro S&D] for modifying or destroying the drone sensed, field verified, spectrotemporal forecasted, *Anopheles,* larval habitats; and 4) Determine the effects of the intervention by using blood parasite levels [Micro S&D] in treated patients and suspected local population members in an entomological intervention site in Gulu District, in Northern Uganda which is one of the malarious regions globally.

2. Methodology

2.1. Study Site

Gulu is a city in the Northern Region of Uganda. The regional headquarters are located in the city of Gulu, which is also the administrative capital of Northern Uganda. As of November 2019, the district was one of the eight districts that constituted the Acholi sub-region, the historical homeland of the Acholi ethnic group. The district is composed of Aswa County and the Gulu Municipal Council. The economic activity of 90 percent of the population in the district is subsistence agriculture.

The district has been the location of much of the fighting between the Ugandan army and the Lord's Resistance Army. Over 90 percent of the population has returned to their villages after more than two decades of living in what was known as "Internally Displaced People Camps. As a result, little is known concerning the prevalence of malaria, mosquito, larval habitats in many peri-domestic, urban and rural, agro-pastureland areas in Northern Uganda. This presented an ideal opportunity to test the performance of our real-time interactive, web-friendly, drone, dashboard, cell phone, signature architecture in an area where little is still known concerning the seasonal, abundance and distribution of *Anopheles* mosquitoes and the spatial epidemiology of the disease in urbanizing peri-domestic environments, making it conducive to being a study site for larval habitat, forecast signature, scale-up mapping a capture point for implementing real time, district-level, IVM tactics [e.g., Macro and Micro S&D].

2.2. Malaria Transmission in Gulu

In Gulu district, malaria is the leading killer disease among children <5 years. In 2015, the high intensity of malaria infection in Northern Uganda revealed a possible link between malaria and rainfall. However, available information on the influence of climatic factors on malaria are scarce, conflicting, and highly contextualized, and therefore one cannot reference such information to malaria control policy in Northern Uganda,

During the 10 year's retrospective study period, a total of 2,304,537 people suffered from malaria in Gulu district. Malaria infection was generally stable with biannual peaks during the months of June-July and September-October but showed a declining trend after the introduction of indoor residual spraying. Analysis of the departure of mean monthly malaria cases from the long-term mean monthly malaria cases revealed biannual seasonal outbreaks before and during the first year of the introduction of indoor residual spraying. However, there were two major malaria epidemics in 2015 following the discontinuation of indoor residual spraying in late 2014. Children <5 years of age were disproportionally affected by malaria and accounted for 47.6% of the total malaria cases [30].

2.3. Entomological Sampling

Prior to the onset of this study, all households in the intervention an agro-village Akonyibedo in Gulu District were enumerated and mapped, which was used to generate a sampling frame for the entomology surveys.

All households enumerated during the survey were assigned a unique number. A random sample of 120 households was selected to generate a list of households to be approached for recruitment into the entomology survey. From the list, households were selected for participation in the human landing catches, pyrethrum spray, exit trap collections, and environmental measures (Figure 1). A separate list of random households was selected to generate a list of households to be approached for recruitment into the study being conducted under a separate protocol. The households of all local villagers 16-22 recruited into the cohort study were approached for selection for implementing Macro and Micro S&D, real time, IVM strategies.

Mosquitoes were sampled using miniature CDC light traps (Model 512; John W. Hock Company, Gainesville, Florida, USA) positioned 1m above the floor at the foot end of the bed where a person sleeps under an ITN. Traps were set at 19.00h and collected at 07.00h the following morning by field workers. If the trap was set up in the intended house, the trap was moved to the nearest similar house after obtaining written informed consent from the head of household or an adult household representative. If the occupant did not spend the night in the selected room or the trap was faulty, the data were excluded from the analysis. The number was determined, and the presence of LLINs was recorded. Each night approximately 12 traps were set for 4 nights in each week. The 120 cohort study houses were sampled every other week during the study.

2.4. Pyrethrum Spray and Exit Trap Collections

Randomly selected houses were sprayed using an aerosol of non-residual pyrethroids with a piperonyl butoxide synergist each month. These sprays were combined with exit traps placed over the windows of the houses to capture any escaping mosquitoes. In each site, 10 households were randomly selected for the spray collections from the entomology recruitment list generated from the enumeration database in each site. The same 10 households were sampled one day every 4 weeks. Written informed consent from the head of household or an adult household representative was obtained prior to conducting the pyrethrum spray and exit trap collections. Sampling schedules are shown in Table 1.

Table 1. *Sample timetable of monthly activities.*

Activity/site	M	T	W	T	F
Week 1					
Human landing catches (2 houses/site)	X	X	X	X	
Light trap installation (12-13 houses/night; 50/week)	X	X	X	X	
Processing of HLC specimens (identification, Sp ELISA)		X	X	X	X
Light trap catches (2 houses/night)	X	X	X	X	
Processing of LTC specimens (identification, Sp ELISA)		X	X	X	X
Exit trap installation (2 houses/site)	X	X	X	X	X
Exit trap collection (2 houses/site)	X	X	X	X	X
Pyrethrum spray catches (2 houses/site)	X	X	X	X	X
Processing of ETs & PSC (identification & BM ELISA)		X	X	X	X
Week 2					
Human landing catches (2 houses/site)	X	X	X	X	
Light trap installation (12-13 houses/night; 50/week)	X	X	X	X	
Processing of LTC specimens (identification, Sp ELISA)		X	X	X	X
Week 3					
Human landing catches (2 houses/site)	X	X	X	X	
Light trap installation (12-13 houses/night; 50/week)	X	X	X	X	
Larval surveys of study site	X	X	X	X	X
Week 4					
Human landing catches (2 houses/site)	X	X	X	X	
Light trap installation (12-13 houses/night; 50/week)	X	X	X	X	

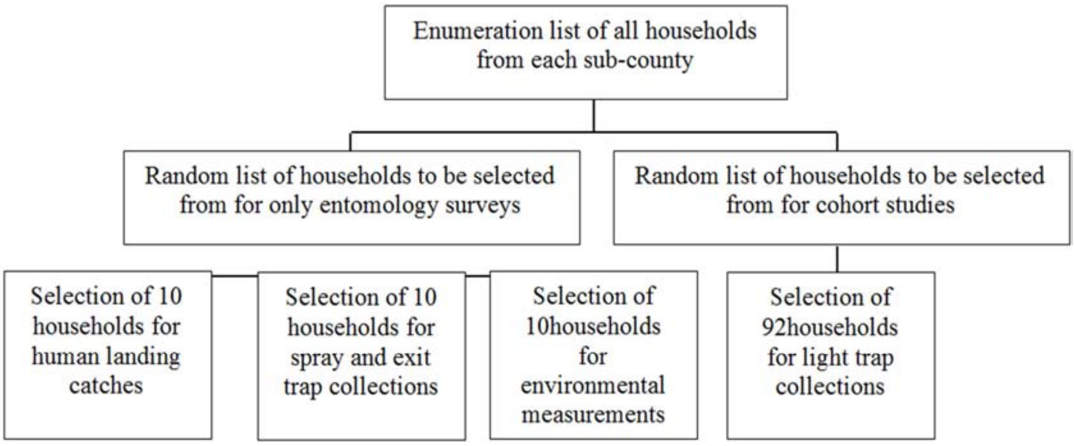

Figure 1. *Sampling frame for random selection of household for entomology surveys in Akonyibedo Village, Gulu, Uganda.*

2.5. Methods

Collection took place between 06.00-08.00h. The number of children and adults who slept in the house the previous night was determined and the presence of LLINs was recorded. White sheets were spread on the floor and over the furniture in the house. Two field workers, one inside the house and one outside, sprayed around the eaves with 0.025% pyrethrum emulsifiable concentrate with 0.1% PBO in kerosene. The fieldworker inside the house then sprayed the roof and walls. The house was closed for 10 minutes, after which the white sheets were brought outside (where there is sufficient light), and dead mosquitoes were collected from the sheets and transferred to the field laboratory on moist filter papers in Petri dishes for identification and processing.

To collect house-leaving mosquitoes, window exit traps were set at 18.00h and collected between 06-07.00h the following morning. Mosquitoes from each trap were put into paper cups separately and transferred to the field laboratory for processing. Mosquitoes were provided with sugar solution for 12 hours from the time of collection. Parity dissections were performed on 500 of each species each month at each site.

2.6. Larval Surveys

The study site was surveyed for water bodies each month. Site coordinates were recorded using a Garmin eTrex 10 Worldwide Handheld GPS Navigator. Purposeful sampling was conducted to maximize the collection of the aquatic stages of mosquitoes using a 350-ml dipper (Clarke Mosquito Control Products, Roselle, IL). At each georeferenced, sentinel site, *Anopheline,* aquatic habitat, 10 dips were made in places likely to harbor mosquito larvae, such as around tufts of submerged vegetation or substrate, edges of water bodies, and around floating debris. In extensive water bodies, dipping was carried out over a 100-m walk. Larvae were classified either as *Anophelines* or *Culicines*. *Anopheles* larvae were stored in 100% ethanol, which was refreshed on reaching the laboratory. Randomly selected subsamples of *Anopheline* larvae selected during the routine mapping of the area sand sibling species of the *An. gambiae* complex was identified by amplification of ribosomal DNA using polymerase chain reaction (PCR).

The depth of water of an aquatic, sentinel site, *Anopheles,* larval habitat was measured from different places depending on the size of the habitat using a meter stick, and the average depth was taken. The distance to the nearest homestead was measured using a tape measure for less than 100 m and estimated if more than 100 m. Distance was then categorized into four classes: (1) ≤ 100 m, (2) 101 to 200 m, (3) 201 to 300 m, (4) 301 to 400 m. Surface debris, presence of algae and emergent plant coverage were determined based on visual observation. Vegetation cover was visually observed and expressed as open (no vegetation), tree (for the presence of large trees within a range of 10–15 m where shade and foliage could reach), and shrub (woody plants smaller than a tree within 10–15 meters). Habitat perimeter was measured using a tape measure and classified as < 10 m, 10–100 m, and > 100 m. Habitat stability was expressed in terms of the length of time the habitat contained water after the rain. A habitat was considered temporary if it held water for 2 weeks or less and permanent if it held water for more than 2 weeks after rain. Though larval sampling was taken on monthly basis, the area was inspected for the presence or absence of rain continuously. Turbidity was measured by placing water samples in glass test tubes and holding them against a white background, and categorized into three levels: low, medium, and highly turbid. Light intensity was visually categorized as sunlit if the habitat received full sunlight that could occur throughout the day, otherwise the site was described as shaded. The substrate type was categorized as mud, stone if the pool was lined with stones that were large in size (rocks generally larger than 10 cm in diameter) and gravel when the stones were small in size but larger than sand. Water temperature was recorded using a water thermometer at the time of collection, and pH was measured using pH indicator paper. Rainfall of the study area during the study period was obtained from Ugandan National Meteorological Agency.

Larval breeding habitats and a number of immature *Anopheles* mosquitoes sampled were described using tables. Correlation analysis was used to investigate the relationship between pH, temperature, and water depth to the *Anopheles* larval density. *Anopheles* larval density was determined as the number of *Anopheles* larvae (early or late) divided by the number of dips taken from each larval habitat. Larval density was log-transformed $\log_{10}(x + 1)$ to improve the normality of distribution. Multiple regression analysis was used to identify the environmental variables associated with the occurrence of *Anopheles* larvae. Mann–Whitney *U* test was used to compare samples with two variables; the presence of algae (presence or absence), habitat permanency (temporary or permanent), surface debris (present or absent), the intensity of light (sunlit or shaded), and water movement (still or flowing). Kruskal–Wallis H test was used to compare samples with more than two groups: water turbidity, water perimeter, distance to the nearest house, canopy cover, emergent plant coverage, habitat type, and substrate type. These non-parametric tests were used to compare larval densities from sites with different habitat characteristics. Data were analyzed using IBM SPSS statistical for Windows (IBM corp., Armonk, NY), version 20.0. Values were considered significantly different if $p < 0.05$ for all the tests.

A large number of specimens were collected from the different aquatic, sentinel sites, larval habitat sites, and from the different collection methods. All *Anopheles* were identified taxonomically to species level. To process the mosquitoes, we implemented a systematic procedure for labeling and recording the specimens, which included the following information: 1) area where the samples were collected, 2) house number (which was linked to GIS data), 3) method of collection, 4) date of collection, and 5) the serial number of the specimen. When processing the specimens, labels were written in pencil and placed with the relevant specimens in Eppendorf tubes, and similar information was recorded in a register for easy data entry and cross-checking.

2.7. Remote Sensing Protocol

Drone surveys were carried out using a DJI Phantom 4 Pro (DJI, Shenzhen, China) quadcopter fitted with a DJI 4K camera (8.8 mm/24 mm; f/2.8; 1" CMOS; 20 MP) for conventional RGB signature, capture point, LULC imagery collection and a 3DR Solo (3D Robotics, California, US) quadcopter fitted with a Parrot Sequoia sensor (Parrot, France) which is composed of single-band cameras (Green, Red, Red Edge and NIR of 1.2 MP for multispectral imagery collection. The flight plan was programmed with Pix4D Capture app in an iPad Mini 4 (Apple, California, US). The connection between the controller and DJI Phantom 4 Pro and 3DR Solo was set up using DJI GO 4 app and 3DR Solo app, respectively. For approximately 30 minutes, the drone flew over the entomological, intervention site using the high-end, radio-controlled, and camera-equipped for urban, agro-village and rural pastureland explorations. The drone was integrated with handheld devices to greatly enhance its capabilities for aerial footage. The multangular drone camera within the kit recorded, stored, and managed the capture point, seasonal, georeferenced, sentinel site, signature data in the drone dashboard spectral library. A copy of the sentinel site, *Anopheline,* larval habitat LULC data, and spectral imagery was stored in the on-flight computer and concurrently transmitted down to the ground stations via Wi-Fi communication in real-time employing the cloud-based, DroneDeploy™ platform DroneDeploy software.

2.8. Orthomosaic Construction

The photogrammetric processing (e.g., *Anopheline,* larval habitat, sentinel site, reflectance, surface measurements based on photographs) was conducted in AgiSoft Photoscan Pro (https://www.agisoft.com). The resulting UAV imagery was imported into Photoscan and processed to construct an orthomosaic (i.e., georeferenced, overlapped, sentinel site, LULC images with correction for topographic distortions) for the entomological, intervention site. The position of the drone at the time of image capture for each *Anopheles,* larval habitat, sentinel site photo was recorded automatically by the on-board GPS; hence the orthomosaic was georeferenced without the need of Ground Control Points (GCPs) [see Figure 2].

The standard procedure used was: photo-alignment (accuracy: highest; generic preselection active, reference preselection active; Keypoint limit: 80,000; adaptive camera model fitting active); (2) dense cloud building (quality: high; depth filtering: aggressive); (3) elevation model (geographic projection using; resolution of 0.1 m and 0.02 m per pixel for the RGB and multispectral images respectively; interpolation: extrapolated; all georeferenced, *Anopheline,* larval habitat, capture point classes to generate digital surface model); (4) orthomosaic building (input surface:; blending mode: mosaic; resolution of 0.1 m and 0.02 m per pixel for the multispectral, georeferenced, aquatic, larval habitat, sentinel site, land cover UAV seasonal, images respectively.

Once the drone signatures were captured, it was real-time transferred into the ArcGIS-AI Interface Kit™, where a stochastic interpolation algorithm ran the signature over the entire district using commercial high-resolution satellite data (46 cm Wv-2, visible and NIR wavebands) to identify unknown larval habitat aquatic foci at the entomological, intervention site [Figure 3]. This real-time scaling up RBG signature, sentinel site, *Anopheline,* larval habitat, grid-stratified, LULC mapping was based on the Faster R-CNN algorithm being applied to real-time georeferenced, capture point, sample, estimator datasets which included DGPS indexed component video data. The analog signatures and priority information extracted [Figure 4] from the capture points were used for optimizing seasonal, field control, sentinel site, imaging and entomological sampling operations. For example, when a user (e.g., trained local district-level, vector control officer) submitted a query of *Anopheles* larval habitats and video clip, the system retrieved a ranked list of visually similar district, aquatic, larval habitat types with GPS coordinates in real-time.

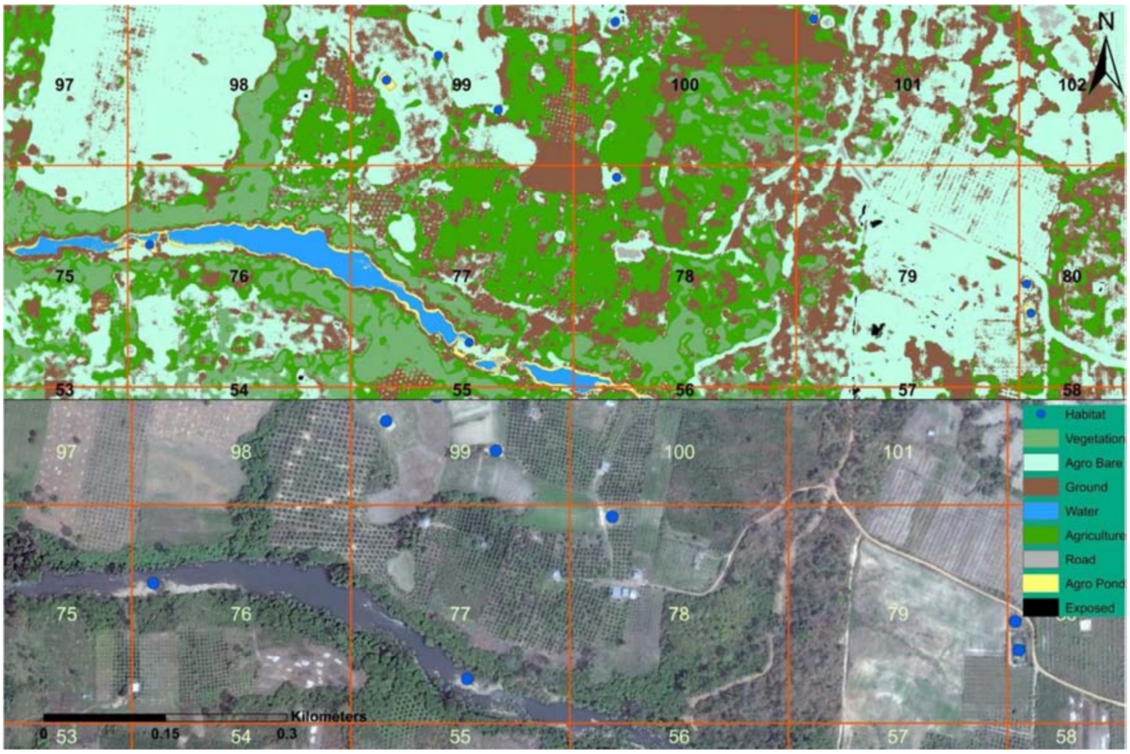

Figure 2. *Supervised classification of 7 digital surface model classes identified in a drone image: open water, emergent aquatic vegetation, agro-pond, trees/bushes, grass, bare soil, untarmacked roads/paths, and agriculture; the sentinel site markers are delineated in blue font.*

Figure 3. *RGB sentinel site signatures in the spectral histogram a) An arabiensis rice tiller habitat b) An. gambiae hoof print habitat c) An. funestus river stream bed habitat d) An. gambiae commercial ditch habitats e) temporary An. gambiae s.l. rain pools f) An. funestus cultivated swamp.*

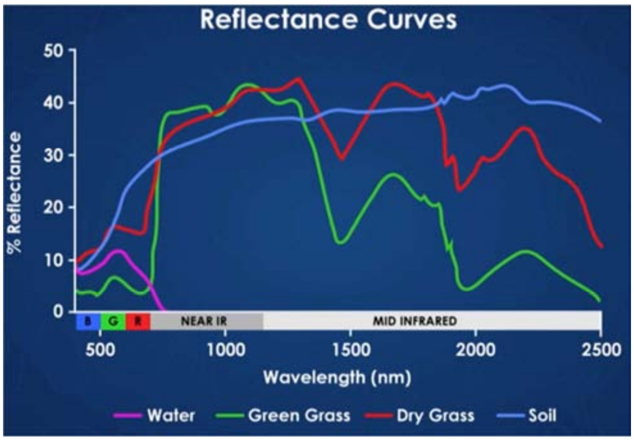

Figure 4. *Spectral histogram RGB sentinel site signature of a georeferenced, sentinel site. An. gambiae commercial ditch habitat.*

Leveraging USFs research team's expertise, the app interface and experiences were built employing the Unity game engine software and Vuforia 6 SDK. The Vuforia Area Target Creator application allowed us to easily generate an Area Target using a depth-enabled mobile device, [iPads, and iPhones]. Vuforia is an augmented reality software development kit (SDK) for mobile devices that enables the creation of augmented reality applications. [https://liu.diva-portal.org/smash/get/diva]. This developer used computer vision technology to recognize real time drone images and 3D objects. This image registration capability enabled us to position and orient virtual, *Anopheline,* larval habitat objects, [e.g., canopy gap understory and midstory vegetation, vertical foliage distributions etc.] in relation to the sentinel site, breeding site, aquatic foci when they were viewed through the drone camera of a mobile device. The virtual object tracked the position and orientation of the habitat image in real-time so that the viewer's perspective on the object corresponded with the perspective on the georeferenced, mosquito habitat target.

3. Results

The results of larval sampling and the types of larval habitats that were productive in the study area are presented in Table 2. Eight sentinel habitat types were identified in the entomological intervention study site, including borrow pits, hoof prints, rain pools, pools at river edges, pools in the bed of drying river, rock pools, tire tracks, and swamps.

Table 2. *Density of Anopheles larvae in different sentinel site habitat types in Akonyibedo village.*

Habitat type (n)	Total larval count	No. of larvae/dip (Mean ± se)	Total pupal count	No. of pupae/dip (Mean ± se)
Borrow pit	219	14.3±8.6	8	0.5±0.1
Hoof print	193	5.5±1.2	8	0.2±0.1
Rain pool	712	5.5±1.5	84	0.6±0.2
Commercial road ditch	3063	13.0±2.1	148	0.7±0.2
Rice tillers	704	35.2±7.9	70	3.5±0.8
Agro-Pond	1038	32±2.7	51	2.1±0.7
Rock pool	228	6.5±3.4	27	0.6±0.3
Tire track	313	6.4±3.2	22	0.5±0.2
Swamp	79	2.1±0.2	13	0.3±0.1
Quarry	124	19.4±4.1	71	2.2±0.3

* Values in italics for mean larval and pupal density indicate mean larval or pupal density of each sentinel study site

For about 25 minutes, a DJI Phantom 4 Pro drone, high-end, radio-controlled, and camera-equipped, flew over multiple georeferenced, sentinel sites as designated by an entomological vector field control team using the interactive iOS app. The dashboard was integrated with handheld devices to greatly enhance its capabilities for aerial footage and a multangular camera within the kit that recorded, stored and managed the retrieved capture point signature, gridded, LULC reflectance data. A copy of the larval habitat data and spectral imagery was stored in the on-flight computer and in the app, which was concurrently transmitted down to the ground stations via Wi-Fi communication in real-time employing the Drone-Deploy^{TM} software. ArcGIS Configurable Apps provided a suite of app templates that allowed creating a web app from the signature sentinel site LULC maps and from the UAV scenes without having to write a code. By leveraging an app template and choosing a few options, we were able to interact with the UAV real time maps with the field sampled entomological data.

For testing, we flew the UAV over the sentinel sites. During these wayward flights, 11 videos with a total of 25 minutes were collected. The total number of frames extracted was 1,058, with 82% of them containing at least one potential *Anopheles* larval habitat.

Real-time, web-based, interactive, geospatial analytical geoprocessing tools within the drone dashboard were also employed to carry out inspections of reflectance, anomalous, seasonal, landscape characteristics of potential *Anopheles* larval habitats, or potential intervention sites using video analog, LULC data with seasonal, georeferenced, sentinel site, capture point, aquatic signatures previously obtained. These LULC types were then labeled [Figure 5].

The data was exported in real-time to a handheld device (e.g., tablet, iPad, mobile phone); so that control personnel could view the multi-directional footage using a mobile Apple handheld devices (i-Pad) which provided DGPS coordinates. All habitat LULC objects and their signatures were easily identifiable.

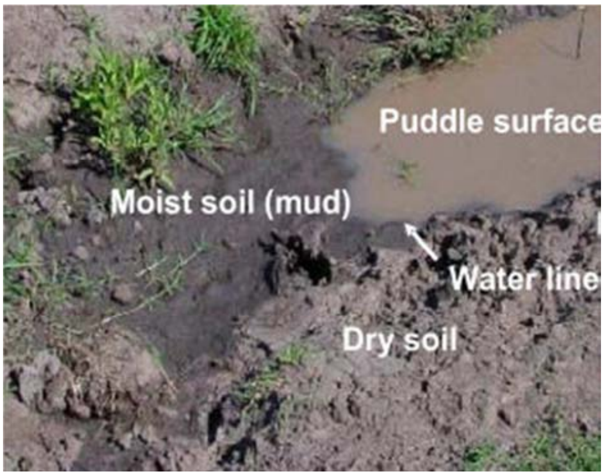

Figure 5. *Selected experimental Anopheles larval habitat signatures assembled in real-time from multiple experimental georeferenced drone sensed sentinel site, capture points.*

We then tested the scalability of the ArcGIS-AI dashboard iOS app for detecting potential peri-domestic aquatic habitats from drone video capture point in a sub-county geolocation [Akoyibedo village] in Gulu District, across seasons. Once the signatures were captured it was real-time transferred into the ArcGIS-AI Interface Kit™, where an interpolation algorithm ran the signature over the entire district using commercial high-resolution satellite data (i.e., 46-centimeter Wv-2 band data) to identify previously unknown aquatic, *Anopheles* larval habitats. This real-time, scale-up, signature mapping of the capture point, *Anopheline,* larval habitats was based on the Faster R-CNN algorithm being applied to real-time imaged, sentinel site, seasonal, signature, sample datasets which included the RGB component video.

. Drone images were analyzed to predict potential *Anopheline* larval habitats first in village and then throughout the district, using the app [see Figure 6 a, b, c and d]. We tested the scale-up of a georeferenced capture point by applying the previously discussed methods, including validation, at 65 sites across Gulu district during each of the three seasons. Of the 65 sites predicted to be suitable by the app, a criterion for success here was that 65 of the breeding sites should be found to contain *Anopheles* larvae (95% Confidence interval (CI) 100%).

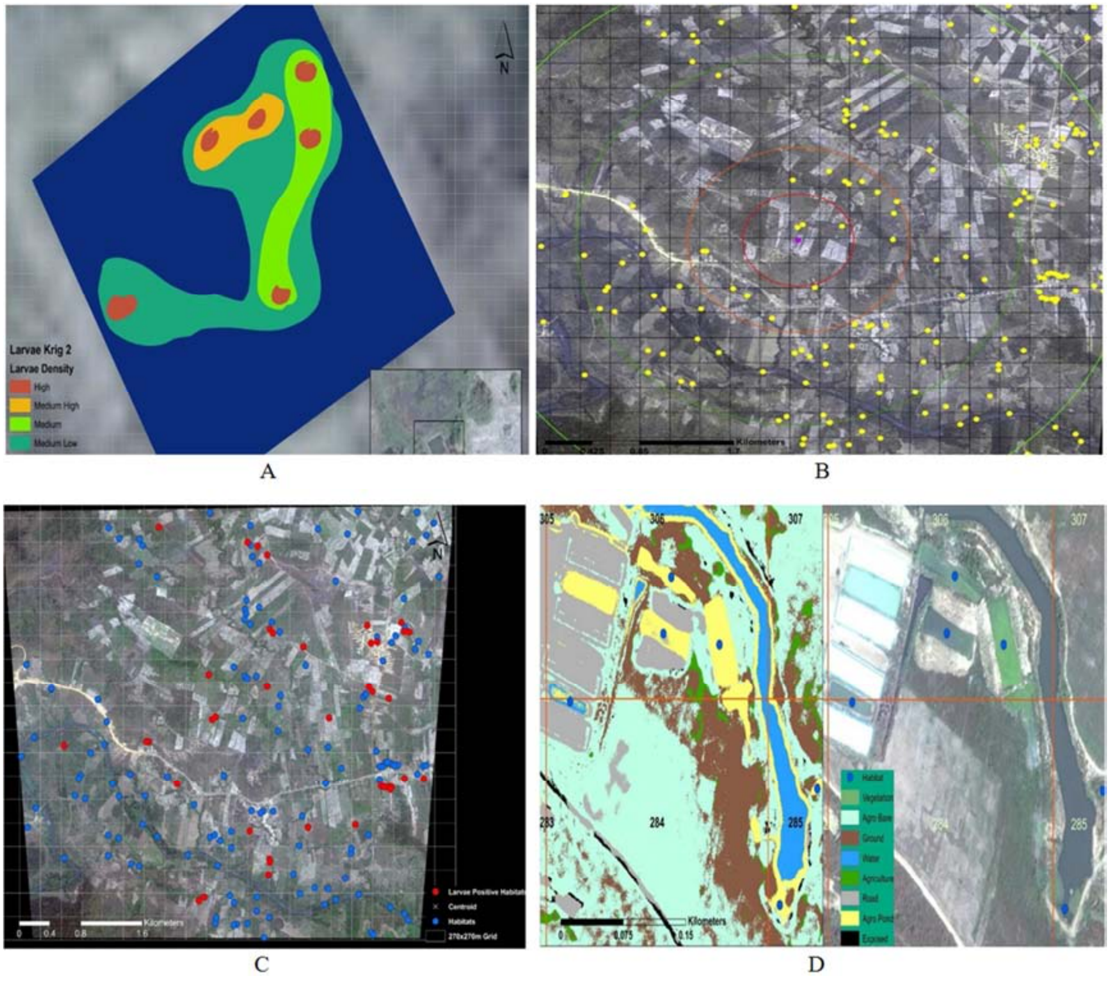

Figure 6. *a) Drone classified kriged sentinel site signature map of an An. gambiae s.l. agro-pond RGB habitat signature using Wv-2 data b) agro-pond habitats in Gulu district from scaled up village capture point breeding site c) identified habitats with larvae and without larvae generated by interpolating the signature of Anopheles larvae over the agro-pond drone predicted habitats d) Field validated habitat targeted for real time drone larviciding.*

These unique identifiers of aquatic habitat spectral signatures were then used to predict *Anopheline* larval habitats along un-surveyed district-level regions. We tested the scale-up of the ArcGIS-AI dashboard app from drone video to the district level across seasons using Wv- 2 30-centimeter data. We were able to then field verify unknown *Anopheline* breeding sites, capture points [Figure 7].

Figure 7. *Typical scaled-up district-level Anopheles gambiae s.l. breeding habitats in Gulu district predicted by interpolated sentinel site signatures in the drone AI-GIS.*

Weekly baseline data collection for both epidemiological and entomological data were collected in January 2021, Seek and Destroy intervention was carried out in February and March; and weekly surveillance was conducted from April up to June 2021. To confirm that the *Anopheline* larval habitat modification process described above could be a viable tool against malaria, both entomological and epidemiological baseline data for adult mosquito biting rates were collected for control reference purposes, which was subsequently compared to data post-intervention. Our preliminary results conducted in Akonyibedo village showed that from three weeks to two months after the intervention, a drastic decline in the number of indoor resting adult *Anopheline* mosquitoes occurred, based on routine monthly pyrethrum spray catch (PSC) entomological surveillance. Two months after the S & D intervention approach, there was a steady decline in blood malaria parasite positive cases as examined during the monthly routine community malaria test and treat outreach, conducted by our joint teams together with the health staff from the local health facility.

For the entomological surveillance baseline data, still within the identified high adult *Anopheles* biting and blood malaria positive parasite areas, 120 households were randomly selected for PSC procedures to collect adult indoor resting *Anopheles* mosquitoes. Using knockdown insecticides, groundsheets, and dissecting microscopes, Mr. Denis Loum, a local entomologist and district control officer, identified, classified, and established species population density and examined sporozoite rates in all the collected indoor-resting adult *Anopheline* mosquitoes for baseline data before the intervention, then repeated this procedure after the intervention to compare results,

For epidemiological surveillance, a field team visited the local nearby health facility serving the intervention community; for collecting out-patient malaria case reporting data and to tease out the areas within the community with the highest malaria cases on record. With the help of district medical entomologists and laboratory personnel, Dr. Martha Kaddumukasa, identified high malaria case areas within the intervention community and conducted random blood samplings, categorically, with varying age and group clusters. Blood samples were taken and analyzed for the rampant presence of malaria blood parasites. With a collective approach, in line with Uganda's Ministry of Health of Test and Treat malaria policy, all confirmed positive malaria cases were treated (as an integral outreach program usually included on the local health facility work plan). This data was recorded as a baseline before the S & D approach intervention, which was then compared with fresh data after the intervention. All malaria-related seasonal parameters, including entomological, parasitological, socioeconomic, and case management data, were tracked by household and mosquito source identifier numbers.

Water bodies were identified in the drone sensed imagery, as well as ancillary information for implementing real time larval control activities [e.g., Macro S&D, which involves entirely burying breeding site, aquatic, *Anopheles* foci such as potholes, commercial roadside ditches, temporary rain pools, footprints, tire tracks and other household habitats with soil substrate]. The soil substrates were effective for approximately 120 to 150 days, but a secondary validation was applied employing the ArcGIS-AI dashboard app within 1 week of treatment. Our drones have a sensor-controlled drop-down appendage which was controlled by the cell phone app, which aided in optimally targeting and treating exact geolocations of georeferenced, larger, breeding sites, [e.g., applying.05mg of SAFE insecticide per inoculation to only the open sun lite exposed sides of a 10meter (m) x10m, rock pit, quarry, seasonal, *Anopheline,* aquatic, habitat foci where the larvae/pupae reside] [Figure 8]. The real time control technique was extremely cost-effective as we applied only minimal amounts of the insecticide (SAFE) to the real time, drone mapped, field verified, remotely targeted, breeding sites [Figure 9]. [e.g., inoculations only on permanent or semi-permanent, uncanopied, pre-flooded tillers in a mature paddy field hence avoiding intermittent, dry post-harvested foci] with surgical precision as compared with non-real-time, drone applied, blanket treatment, insecticide spraying since we applied the SAFE at a height less than a foot [i.e., 0304m] (no spillage, no droplet drift) above the targeted habitat which allowed implementing Macro S and D [Figure 10].

Figure 8. *Targeted spray in an agro-field Anopheles larval habitat in Akonibedo village.*

Figure 9. *UAV Maps of Targeted spray in an agro-field Anopheles larval habitat in Akonibedo village.*

Thereafter we tested the scalability of the smartphone, dashboard app for detecting potential aquatic *Anopheles* habitats from drone video using high-resolution Wv-2 46 centimeter, gridded, [270 m x 270m] satellite data. Field validation revealed that of 65 predicted breeding site habitats, all contained *Anopheles* larvae/pupae revealing a sensitivity and specificity approaching 100% for each season.

We continued to signature, drone seasonal, forecast map all treated sub-county, capture point, district-level, intervention sites every 7 -14 days to establish if new aquatic foci had occurred and treated those habitats. In so doing, we were able to ascertain valuable, district-level, seasonal, entomological information [e.g., georeferenced routes to a large, algae, matted cultivated, swamp habitat adjacent to an agro-pastureland village homestead population; precise drying temporal, sample frames of lagoons, transient pools and flooded, man-made hole, sentinel sites, etc.] for optimal, real time, seasonal, drone vulnerability signature forecast mapping and treating *Anopheles,* capture point, breeding site, aquatic foci. In 31 days, post-Macro and Micro S&D intervention there was zero vector density, indoor, adult, female, *Anopheles* count as ascertained by PSC at the intervention site [Tables 3 and 4]. After a mean average of 62 days, blood parasite levels revealed a mean 0 count in treated malaria patients [Figures 13ab and c, Figure 14 a and b].

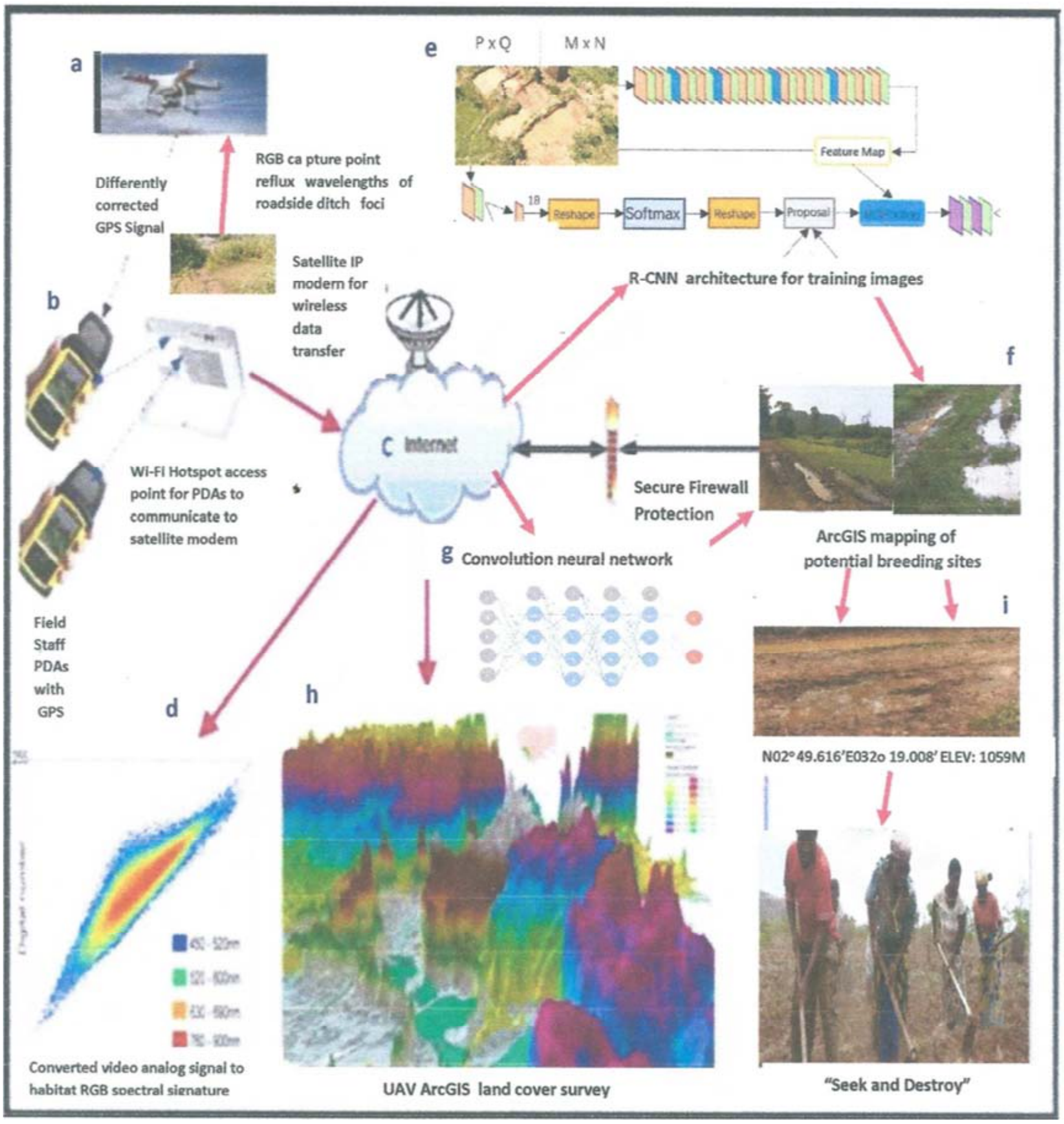

Figure 10. *A real time UAV, Anopheline habitat mapping for implementing "Seek and Destroy" (a) An RGB video analog seasonal Anopheles habitat captured in a UAV spectral library (b) Drone captured data transmitted via Wi-Fi hot spot for scaling up to a larger epi-entomological intervention site employing a hand held device (c) remote data synchronization into an Internet Cloud d) time series habitat spectral signature (e) R-CNN model constructed employing all annotated images (f) Real time ArcGIS cartographic data analysis to locate sources of breeding sites (g) Convolution neural network for assigning learnable weights to various habitat objects in capture point mages h) aerial habitat detection (h) mapped unknown Anopheline foci by GPS locations (j) mobilization of local trained villagers for conducting "Seek and Destroy".*

Table 3. *Pre and Post Seek and Destroy Intervention in Akonyibedo Village.*

Monthly adult mosquito entomological surveillance data (Taken from 120 households)					
Year	**Month**	**Female An. Gambae s.l**	**Female An. Funestus**	**Female Culicines**	**Activity**
	January	412	288	113	Baseline
	February	460	312	97	Intervention
	March	681	433	69	
	April	12	22	55	Entomological surveillance
	May	0	3	41	
	June	0	0	12	

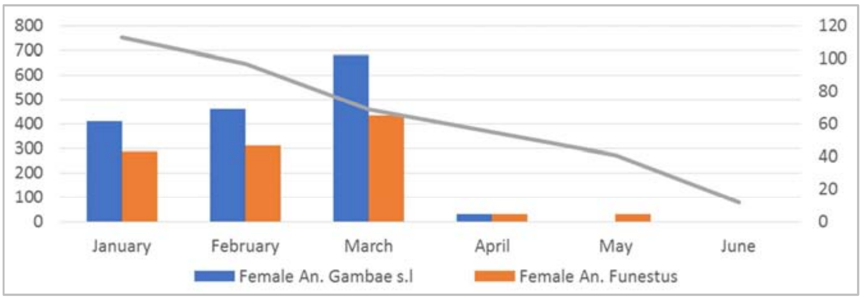

Figure 11. *Monthly Entomological Surveillance Data taken from 120 housholds.*

Table 4. *Pre and Post S & D intervention in Akonyibedo village.*

Monthly Malaria tested and treated cases (Taken throughout the village)				
Year	**Month**	**Total tested**	**Positive and treated**	**Activity**
2021	January	2459	1984	Baseline
	February	3881	2560	Intervention
	March	2777	1955	
	April	1233	134	
	May	971	21	Epidemiological surveillance
	June	533	2	

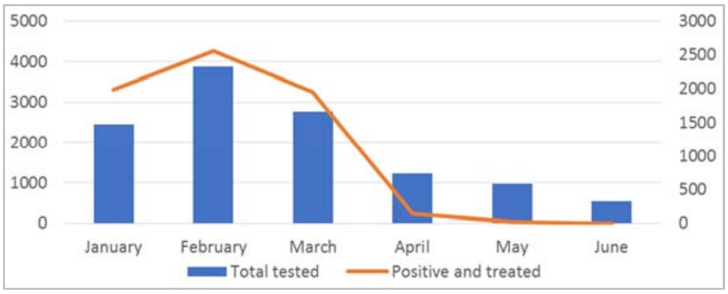

Figure 12 *Montly malaria blood parasite tested and treated cases taken throughout the village.*

Figure 13. *ab and c Adult Anopheles mosquitoes collected using PSC capture method, being identified in a local lab, in Akonyibedo village, Gulu District-Northern Uganda.*

Figure 14 *Epidemiological Surveillance: Local Entomologist conducting community Rapid Test Diagnosis for Blood malaria parasite prevalence in Akonyibedo village June 26, 2021.*

4. Discussion

Our real time technology using a drone-mounted video RBG camera allowed creating a sentinel site signal for efficiently forecast mapping the precise geolocation of *Anopheline* mosquitoes in their most concentrated stages, the aquatic habitat. Coupled with this capability, we developed a means to employ this signature to geolocate other similar, sentinel site, LULC stratified, capture points over the flight path of an unmanned aerial vehicle [e.g., a drone flight time of 10 minutes over a hectare of mature paddy field in Gulu revealed > 5000 previously unknown, seasonal, aquatic, *Anopheles* microhabitat, larval, breeding sites. The drone was integrated with handheld devices to greatly enhance its capabilities for aerial footage. The multangular camera recorded, stored, and managed the capture point, signature LULC, classified data. A copy of the larval habitat data and spectral imagery was also stored in the on-flight computer and concurrently transmitted down to the ground stations via Wi-Fi communication in real-time employing the Drone-Deploy™ software.

We built an interactive, configurable, geo-AI, web-based dashboard, iOS app for optimizing forecast, signature, vulnerability mapping, sentinel sites and for real time identifying and treating unknown capture point, *Anopheles,* breeding site, aquatic foci. We were able to create wayward, maps using the LULC data exported from the DJI Phantom 4 Pro drone, high-end, radio-controlled, and camera-equipped repository database in the dashboard app. Web-based, interactive, spatial analytical geoprocessing tools in the app was subsequently employed to carry out inspections of reflectance, capture point, anomalous, seasonal, landscape characteristics of potential, *Anopheles,* larval habitats, or potential intervention sentinel sites using video analog data employing the archived, RGB indexed, capture point signatures.

We then tested the scalability of the real time, retrieved, sentinel site, RGB signatures from the georeferenced capture point to identify unknown, seasonal, district-level, *Anopheles,* larval habitat, aquatic foci using the web interactive geo-AI app. The app ran a trained deep learning model on an input raster to produce a feature class containing various sentinel site, larval breeding site, capture point objects [e.g., rice tillers in a post-harvest/fallow, *An. arabienis s.s.* paddy habitat] which was subsequently scaled out from the georeferenced capture point to identify unknown breeding sites at the district level. The features were bounding boxes or polygons around the predicted, district-level, aquatic habitats in the app. This tool required a model definition file containing trained model information. The real time, UAV sensed, RGB signature, sentinel site model was trained using a third-party training software [i.e., PyTorch]. The model definition file was an Esri model definition JSON file (.emd) which contained the path to the Python raster function which called to process each sentinel site, aquatic, *Anopheles* larval habitat and the trained binary deep learning model file in the configurable, smartphone app. We trained the deep learning models using sensitive (5-minute maximum wayward UAV flights and processing of RGB signature) over a seasonal sampled, georeferenced, *Anopheles*, aquatic, larval habitat, capture point and derived information products [e.g., forecasted, district-level maps of potential, unknown, seasonal breeding site aquatic foci] using the ArcGIS Pro and ArcGIS API for Python and scale up the processing of ArcGIS Image Server in the app. Detection geoprocessing tools [e.g., convolutional neural networks (R-CNN, Region-Based Convolutional Neural Networks], Fast R-CNN and Deep Learning tools in ArcGIS Pro long with other infused geo-AI remote sensing, object-based algorithms in the app were able to precisely, forecast, signature map seasonal, *Anopheles*, aquatic, larval habitat geolocations by scaling up a database of UAV imaged, sentinel site, capture point, georeferenced signatures using Wv-2 data.

Of the 65 sites in the entomological intervention site predicted to be district-type breeding site, aquatic habitats by the model, all (100%) were found to contain *Anopheles* larvae during field verification. In contrast, none of the 50 sites not predicted by the model but deemed to be potential district-level habitats by the entomologist accompanying the verification team contained *Anopheles* larvae. Together, these data suggested that the real time, UAV, signature, interpolation model constructed in the configurable, interactive, smartphone app exhibited a sensitivity and specificity approaching 100% for the prediction of *Anopheles* larval sites in Gulu District.

Simulation studies in a real time UAV platform may be used to generate a real time, LULC classifiable, drone sensed, RGB, sentinel site, signature, iterative, interpolative methodology employing geo-AI technologies infused into a web configurable interactive smartphone app for optimally identifying unknown, seasonal, aquatic, *Anopheles* (*gambiae, s.l. funestus s.s. and arabiensis s.s*) larval habitats throughout districts in Uganda and in other countries where malaria is endemic. We integrated external deep learning model frameworks using PyTorch in the smartphone app; in so doing, we were able to employ a model definition file multiple times to detect seasonal LULC change over time for optimally identifying district-level, seasonal, aquatic, *Anopheline*, larval habitat breeding sites. We were able to generate a polygon feature class in the app showing the geolocation of detected unknown habitats at the district level using additional satellite workflow analyses. A deep learning model package (.dlpk) in the app contained the files and data required to run deep learning inferencing tools for object detection and for remote image classification. The package was uploaded to the portal in the app as a DLPK item and used as the input to multiple deep learning raster analysis tools for parsimoniously stochastically interpolating the sentinel site signatures. The creation and export of training samples were all conducted in the app employing standard training sample, real time, UAV dashboard, 3-D generation tools. The deep learning, entomological, real time, forecastoriented, RGB signature model was trained with the PyTorch framework employing the Train Deep Learning Model tool. Once the UAV model was trained, we used an Esri model definition file (.emd) in the app to run the geoprocessing tools to detect and classify the seasonal, georeferenced, sentinel site, larval habitat, LULC stratified, capture point features in the satellite imagery for identifying unknown, scaled-up, district-level, aquatic, *Anopheles* habitats.

It is important to note that when installing the deep learning framework Python packages into a real time iOS app platform, an error can occur when adding the Esri model definition file to the geoprocessing tools. Fortunately, ArcGIS is an open, interoperable platform that allows the integration of complementary methods and techniques in several ways: through the ArcGIS API for Python, the ArcPy site package for Python, and the R-ArcGIS Bridge. Here ArcGIS API for Python integration allowed generating a configuration file in JSON format that provided a dataset of sentinel site, UAV sampled, *Anopheles,* larval habitat, interpolative, signature parameters for attaining deep learning model inference in ArcGIS. The EMD included model properties, and metadata which was accessible from the Python raster function (e.g., the location of the trained signature model file).

With the ArcGIS Image Analyst extension, an entomologist, clinician or, other research investigator may construct entire deep learning workflows with real time, UAV imaged, georeferenced, seasonal, aquatic, insect, vector arthropod, larval habitat, signature imagery in ArcGIS Pro. The geoprocessing tools in ArcGIS Pro can prepare UAV sentinel site, RGB, imagery training data, and then conduct scaled-up, capture point, real time, habitat detection using CNN architecture for geometric matching, field verifying and treating breeding sites, seasonal aquatic, vector arthropod foci using high-resolution pixel classification in a smartphone app. By combining powerful built-in tools with a machine learning package [e.g., scikit-learn and TensorFlow in Python], spatial validation, geoenrichment, and visualization of scaled-up, sentinel site, spectrotemporal stochastically interpolatable. capture point, aquatic, *Anopheles,* larval habitats can be sentinel site, signature forecasted for cost-effectively treating geolocations of gereferenceable, unknown district-level, breeding sites using a web-configurable app. For example, TensorFlow may provide a collection of workflows to develop and train UAV sensed signature models using JavaScript, which may easily be deployed in the cloud, on-prem, in the browser, or on a handheld device regardless of language employed for remotely targeting exact natural and clear, water bodies such as *Anopheline* riverbed pools with sandy substrates and still water.

We created a large spectral library of georeferenced, aquatic, *Anopheles,* larval habitat, capture point, sentinel site, RGB signatures as well as for other vector species of mosquitoes [*Culex quinquefasciatus, Aedes aegypti*] in Gulu. We generated data-driven attribute transformatios using deep feature spaces in the smartphone app for archiving the breeding site, sentinel site, LULC classified capture point, seasonal, UAV retrieved RGB, spectral signatures. We can now go into an unknown district-level area and locate the precise geolocations of productive aquatic, seasonal habitats where vector larvae are clustered for prioritizing treatment [i.e., real time drone larviciding target site of a an irrigation canals, seepage from water pipes, neglected wells, artificial containers, man-made ditches etc.]. We have also added the appropriate means within this real time IVM tool to deliver, with surgical precision, an environmentally friendly control tactic (e.g., burying and monitoring of a real time, drone mapped, field-verified, temporary, sunlit, clear and shallow, fresh water, *An. gambiae s.l.,.* isolated habitats occurring in uncultivated swamp margins], i.e., Macro S&D). An added benefit of our unique, geo-AI, real time, UAV, habitat signature, forecasting and delivery system is that it can be used to scale up to eco-geographically locate with precision productive, seasonal, capture point, *Anopheles,* breeding site, aquatic foci from satellite data. Deep convolutional neural networks embedded in an interactive smartphone app can perform spectral classification tasks such as habitat sentinel site, visual object categorization. This allows a smartphone device to establish the occurrence abundance and distribution of all productive, *Anopheles*, mosquito habitat breeding site geolocations seasonally [e.g., rain pools and water bodies created by the climate change, flooded irrigation canals, seepage from water pipes, neglected wells, artificial containers, man-made ditches etc.] at the district, county, state, provincial or regional, wide level. The expansion of sentinel site, drone and satellite sensed, real time, capture point, aquatic, *Anopheles,* larval habitat, RGB indexable signatures over time due to seasonal or climatic changes expands the opportunity for planning the complex logistical requirements for real time IVM operations and assessments of malaria transmission risks to humans [e.g., Micro S&D for determining the quantitative content of parasites in the blood].

5. Conclusion

Integration of geo-AI, machine learning and deep learning ArcGIS geprocessing neural network application tools in a web-configurable smartphone app, developed through this research permitted novel integration of UAV sensor technology for real time, LULC mapping unknown, georeferenced, capture point, sentinel site, aquatic, *Anopheles,* larval habitat, breeding sites. We constructed and archived surface larval habitat, sentinel site, RGB signatures using autonomous sampling strategies in the smartphone app. Local vector control officers in Gulu District were trained how to build the app for broad-scale district-level, UAV surveillance of signature scaled-up, individual and clustering, capture point, georeferenced, *Anopheles,* sentinel site habitats,. The real time UAV, geo-AI technologies in the dashboard interactive iOS app captured the real time, video analog, sensed, surface, signature sampled, reflectance data and identified LULC properties of unknown breeding sites throughout district-level intervention sites by stochastically interpolating the signature data using sub-meter resolution satellite gridded data. The app recorded the capture point geolocations of a georeferenced, seasonal, aquatic, *Anopheline,* breeding site, larval habitat, capture point geolocation as a pin on a predictive map in seconds which was subsequently field verified by local vector control officers at the entomological intervention site. In 31 days, post-Macro S&D intervention, there was zero vector density, indoor, adult, female, *Anopheles* count as ascertained by PSC at the intervention site. After a mean average of 62 days, blood parasite levels (Micro S&D) revealed a mean 0 count in treated malaria patients.

References

[1] Carrasco-Escobar G, Manrique E, Ruiz-Cabrejos J, Saavedra M, Alava F, Bickersmith S, et al. (2019) High-accuracy detection of malaria vector larval habitats using drone-based multispectral imagery. *PLoS Negl Trop Dis* 13 (1).

[2] Hardy, A., Makame, M., Cross, D. et al. (2017). Using low-cost drones to map malaria vector habitats. *Parasites Vectors* 10 (20).

[3] Kgoroebutswe, T. K., Makate, N., Fillinger, U., Mpho, M., Segoea, G., Sangoro, P. O., Mutero, C. M., Chanda, E., Ntebela, D., Mogopa, M., Mosweunyane, T., & Nkya, T. E. (2020). Vector control for malaria elimination in Botswana: progress, gaps and opportunities. *Malaria journal,* 19 (1), 14.

[4] Musiime, A. K., Smith, D. L., Kilama, M., Geoffrey, O., Kyagamba, P., Rek, J., Conrad, M. D., Nankabirwa, J. I., Arinaitwe, E., Akol, A. M., Kamya, M. R., Dorsey, G., Staedke, S. G., Drakeley, C., & Lindsay, S. W. (2020). Identification and characterization of immature *Anopheles* and *Culicines* (Diptera: Culicidae) at three sites of varying malaria transmission intensities in Uganda. *Malaria journal,* 19 (1), 221.

[5] Jensen, J. R., Introductory digital image processing: a remote sensing perspective. 2005, Upper Saddle River, N. J.: Prentice Hall.

[6] Wikle, CK. Zammit-Mangion, A. and Noel Cressie. Spatio-Temporal Statistics with R, Chapman & Hall/CRC, Boca Raton, FL 2019.

[7] Jacob BG. (2019). Efficaciously targeting unknown deleterious *Aedes aegypti* waste tire larval habitat capture points employing krigable photogrammetric Rayleigh optical depths as a function of sub-meter resolution semi-infinite anisotropically scattering landscape signature spectroscopic frequencies under disproportionate solar exoatmospheric irradiance conditions in q-dimensional Euclidean space in a semi-autonomous unmanned aircraft real-time object-based classifier. *Ann Biostat Biometric App*. Pp. 105. Iris Publishers.

[8] Jacob BG, Loum D, Munu D, Lakwo T, Byamukama E, Habomugisha P, Cupp EW, Unnasch TR. (2021). Optimization of Slash and Clear Community-Directed Control of Simulium damnosum Sensu Stricto in Northern Uganda. *Am J Trop Med Hyg.*

[9] Painsky A, Rosset S (2017). "Cross-Validated Variable Selection in Tree-Based Methods Improves Predictive Performance". IEEE Transactions on Pattern Analysis and Machine Intelligence. 39 (11): 2142–2153.

[10] Jacob B. G. and Novak R. J. (2015) Integrating a Trimble Recon X 400 MHz Intel PXA255 Xscale CPU® Mobile Field Data Collection System Using Differentially Corrected Global Positioning System Technology and a Real-Time Bidirectional Actionable Platform within an ArcGIS Cyberenvironment for Implementing Malaria Mosquito Control. Advances in Remote Sensing; 3 (3): 141-196.

[11] Sit, M. A., Koylu, C. and Demir, I.(2019). Identifying disaster-related tweets and their semantic, spatialand temporal context using deep learning, natural language processing and spatial analysis:. *International Journal of Digital Earth*, 1-25.

[12] Srivastava, S., Vargas Muñoz, J. E., Lobry, S. and Tuia, D. (2018). Fine-grained landuse characterization using ground-based pictures: a deep learning solution based on globally available data. *International Journal of Geographical Information Science*, 1-20.

[13] Sun, Z., Di, L. and Fang, H. (2018). Using long short-term memory recurrent neural network in land coverclassification on Landsat and Cropland data layer time series. International *Journal of Remote Sensing,* 1-2.

[14] Zhang X, Zhou X, Lin M, Sun J. Shufflenet (2018).: An extremely efficient convolutional neural network for mobile devices. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Salt Lake City, UT p. 6848–56.

[15] Zoph B, Vasudevan V, Shlens J, Le QV. (2018). Learning transferable architectures for scalable image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Salt Lake City, UT p. 8697–710.