Identification of Aquatic Habitats of *Anopheles* Mosquito Using Time-series Analysis of Sentinel-1 data through Google Earth Engine

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Keywords: Remote sensing, Malaria, Habitat, Sentinel-1, Segment Anything Model, Google Earth Engine.

Abstract

Malaria, a severe disease transmitted by *Anopheles* mosquitoes, presents a substantial public health concern. Since *Anopheles* mosquitoes thrive in water-rich environments, accurately mapping surface water is essential for assessing malaria risk and managing mosquito populations. This study seeks to identify areas prone to water accumulation, which create habitats conducive to mosquito breeding. Initially, high-risk months were extracted using precipitation and temperature data. Subsequently, the Sentinel-1 Water Index (SWI) was utilized to analyse seven years of monthly Sentinel-1 time-series images via Google Earth Engine (GEE). To enhance our findings, we integrated monthly surface-water maps using a weighted majority voting strategy. Validation efforts included collecting 520 samples, half of which were water bodies identified through field observations and Google Earth Pro, with masks generated using the Segment Anything Model (SAM) algorithm. Object-based evaluation was employed, treating each water body as a distinct entity. The results revealed an overall accuracy of 96.1% and a kappa coefficient of 92.2% in water body detection, underscoring the method's effectiveness. This method, which outperformed other approaches in the domain and machine learning classifiers, is straightforward to implement, rapid, and does not require training data. Furthermore, while field monitoring may be challenging, the findings of this study could aid health authorities in identifying high-risk areas for disease control and prevention efforts.

1. Introduction

Malaria is an important mosquito-borne disease caused by Plasmodium species, is globally responsible for causing mortality of one people per minute and has a devastating impact on people’s health and livelihoods (Abbasi et al., 2023; Wang et al., 2023). It is estimated that 41% of the world population live in the areas at risk of malaria (Catry et al., 2018). According to the latest report released by World Health Organization (WHO), there was an estimated 249 million cases around the world resulting in approximately 608,000 deaths across over 80 countries in 2022 (World Health Organization, 2023). The heterogeneity in malaria incidence and mortality has remained critical in the WHO’s global efforts to control and eradicate malaria that led to the ambitious Global Malaria Program (GMP) with the vision of eliminating 90% of the world malaria burden by 2030 (Wang et al., 2023).

Surface water bodies are important breeding habitats of mosquitoes and the species is strongly dependent on the presence of water for its survival and dissemination (Catry et al., 2018; Ovakoglou et al., 2021). Therefore, providing timely and accurate surface water body maps together with other meteorological parameters is valuable for mapping malaria risk and targeting disease control interventions (Hardy et al., 2019; Ovakoglou et al., 2021).

Remote Sensing techniques have been applied to epidemiology for decades (Catry et al., 2018). Radar-based remote sensing methods seem to be more suitable for monitoring water areas, offering the advantage of uninterrupted data supply, whether day or night, and under any weather conditions. Besides, the principle of using side-looking radar images in mapping water bodies is based on the smooth water surface that act as a specular reflector which is distinct from the surrounding area that act as diffuse reflectors.

The most common environmental predictors of malaria incidence are precipitation, air temperature, humidity and vegetation, of which temperature and precipitation are generally reported as being the most influential (Kalthof et al., 2023; Salahi Moghadam et al., 2015). Precipitation itself does not increase malaria transmission; it leads to pool forming depressions, a factor which is further mediated by the hydrology and geomorphology of an area. The resultant surface water pools increase vector abundance which leads to higher rates of malaria transmission (Kalthof et al., 2023). Additionally, the growth and development of insects rely on environmental temperature, which affects the insect vector's ability to transmit pathogens (Abbasi et al., 2023). The suitable temperature range for *Anopheles* mosquito spans from 15 to 35°C, as indicated by previous studies (Abbasi et al., 2023; Youssefi et al., 2022). If temperature goes beyond the tolerability thresholds, the insect’s growth and development stops and its population decreases (Salahi Moghadam et al., 2015).

Data/information fusion can occur at three levels: data-level, feature-level, and decision-level. Also, there are three stages of aggregation which are measurement level, rank level, and abstract level. Weighted majority voting is one of the methods of abstract level. In weighted majority voting, each classified map is assigned a weight based on its reliability or performance. The final decision is determined by a majority vote, with each map's vote weighted according to its assigned weight. This method ensures that the final decision is influenced by both the number of votes and the weights assigned to those votes (Kittler et al., 1998).

The Segment Anything Model (SAM), recently introduced by Meta AI, is a promptly segmentation system that offers zero-shot generalization to unfamiliar objects and images. This approach has made a substantial impact on various computer vision tasks (Osco et al., 2023), enabling accurate predictions with minimal or no training data. SAM's zero-shot capability allows it to perform segmentation tasks with minimal human input, such as bounding boxes, points, or text-based prompts, thereby reducing the labor-intensive nature of previous segmentation methods (Osco et al., 2023). SAM can be applied to various datasets such as Unmanned Aerial Vehicle (UAV), airborne, and satellite imagery.

Google Earth Engine (GEE) is a powerful cloud-based computing platform that includes massive amounts of open access earth observation dataset and also algorithms that simplifies access and processing for experts and non-experts. Besides, it helps to do time-series analysis by providing fast processing and easy downloading data (Youssefi et al., 2022). Due to the large size of study area, GEE is the best option that will help us with the process load of this large data. GEE provides two APIs to interact with; first is JavaScript API which is accessible through web and the second one is Python API which needs an installation. The method presented in this paper is implemented in JavaScript API of this platform.

The aims of the present study are: 1) To extract high-risk months of malaria outbreak by employing precipitation and temperature parameters for the study region; 2) To detect surface water bodies in the extracted study period for each month individually; and 3) To Merge classification maps by implementing weighted majority voting to benefit from capacities of each classification map and identify high risk areas that has the potential to be *Anopheles* habitat.

The rest of the paper is structured as follows. In Section 2 we give an overview of some of the related works in this area before outlining our materials and proposed method in Section 3. Section 4 shows the results and accuracy evaluation of our method. Finally, in Section 5, conclusions are reached and outlined.

2. Related works

Previous studies have demonstrated that remote sensing imagery can be used to map spatial variations in transmission risk. In 2021, Ovakoglou et al. proposed a method for automatic and regular mapping of surface-water bodies in rice fields and wetlands using Sentinel-1 to control mosquito larvae effectively. Four methods as Otsu valley-emphasis algorithms, classification based on textural feature of entropy, a method using K-means unsupervised classification and a method using the Haralick's textural feature of dissimilarity and fuzzy-rules classification were adapted. Among the above methods Otsu valley-emphasis technique resulted in higher overall accuracy (0.835). The approach of Hardy et al. in 2019 was based on mapping both open and vegetated water bodies using Sentinel-1 to detect malaria vector mosquito breeding habitats for western Zambia. They applied open-source segmentation and extra trees classifier to training data that were automatically derived from JRC Global Water Occurence and SRTM DEM. The result indicated mean overall accuracy of 92%. In 2018, Catry et al. assessed vectors, malaria and the environment in the Amazon region using Sentinel-1. They focused on the potential of SAR capabilities and techniques to optimize vector control and malaria surveillance by detecting man-made water collections and natural wetlands. Finally, they proposed a framework for the production of spatialized indicators and malaria risk maps based on the combination of SAR, entomological and epidemiological data to support malaria risk prevention and control actions in the field. In 2023, Kalthof et al. aimed to investigate whether novel surface water exposure indices, considering malaria dispersal mechanisms, derived from high-resolution surface water data, could serve as stronger predictors of malaria prevalence compared to precipitation. The research involved creating 180 candidate predictors by combining three surface water malaria exposures from high-accuracy and high-resolution water maps of East Africa. By utilizing Boosted Regression Tree models and variable contribution analysis, they identified a subset of strong predictors from the novel surface water exposure indices. The results highlighted the importance of incorporating spatial resolution and specific dispersal mechanisms in surface water predictors to enhance malaria prediction accuracy. Few studies in the field of malaria disease and habitat detection are conducted through GEE. In one research published in 2022, Youssefi et al. estimated high-risk times for three regions in Iran by employing a series of environmental factors affecting the growth and survival of *Anopheles*, including precipitation and air temperature through GEE.

In the field of water body detection, in 2017, Tian et al. introduced a new index based on Sentinel-1 using multiple stepwise regression analysis method. They proposed a simple but robust SWI-based water extraction model (SWIM) derived from Sentinel-1 imagery to extract the spatial distribution of water areas. The advantages of extracting water using Sentinel Water Index (SWI) are that it is quick and more efficient than the other machine learning methods. In addition, the SWI threshold classification method can be applied to different regions during different periods with high quantity accuracy.

3. Materials and method

3.1 Data

3.1.1 Sentinel-1: In this study we used Sentinel-1 between 2017 to 2023 for surface-water detection. The Sentinel-1 data collection in GEE is "COPERNICUS/S1_GRD" which includes interferometric wide swath (IW) mode of ground range detected (GRD) scenes. Also, GEE already preprocessed using Thermal noise removal, radiometric calibration and Terrain correction to generate a calibrated and ortho-corrected product. In this study, the ortho corrected backscattering coefficient product of the single VV and VH channels of Sentinel-1 at the spatial resolution of 10 m at both ascending and descending orbits was utilized. The only preprocessing that remains is the speckle that needs to be removed. To reduce the effects of coherent speckle noise, a median filter was used with a window size of 3 pixels by 3 pixels.

3.1.2 PERSIANN-CDR precipitation dataset: PERSIANN-CDR has provided precipitation dataset for 40 years starting from 1983. In the current study, the monthly PERSIANN-CDR datasets within the study are downloaded for the period of 2017 to 2023 and used to extract rainy months.

3.1.3 Air temperature: To consider temperature factor, the seven-year time series of meteorological data obtained from the Iran Meteorological Organization (IMO) has been used. These data include daily average temperature synopsis data measured at synoptic stations in Sistan and Baluchestan province. Then the average monthly air temperature was calculated from the average temperature per day.

3.2 Study area

The study area, Sistan and Baluchestan Province, is located in the southeast of Iran (Figure 1). This province, due to its subtropical climate, is one of the provinces at serious risk of malaria. Additionally, according to health officials, several other factors caused the outbreak during recent years, including heavy rains and poor detection of new cases in the country (Khammarnia and Setoodehzadeh, 2023).

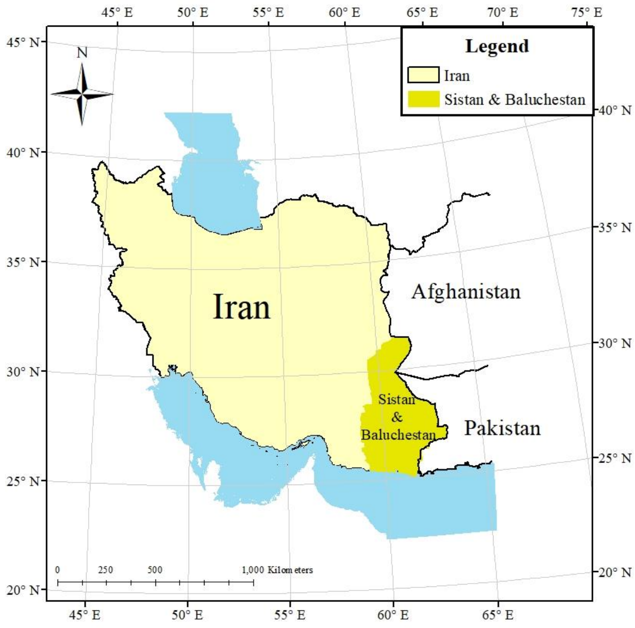

Figure 1. Study area.

3.3 Method

The workflow presented in this paper entailed several steps:
1. Identifying months with elevated risk due to rainfall and temperature patterns, utilizing PERSIANN-CDR and temperature datasets.
2. Gathering Sentinel-1 data to compute the SWI, and pinpointing water bodies by applying a SWI map threshold.
3. Pinpointing high-risk locations by merging monthly water body maps over a period of seven years via weighted majority voting.
4. Assessing the effectiveness of the approach by comparing it with water depression masks produced by the SAM model.

Each of these four steps is explained separately below. Our workflow is illustrated in Figure 2.

3.3.1 Extraction of high-risk periods: To predict potential breeding sites, we first determine the study period and concentrate on high-risk times of the year. By using effective environmental parameters, we can accurately forecast malaria outbreak periods. Precipitation and temperature are crucial in increasing *Anopheles* mosquito populations, influencing both larval stages and the risk of malaria transmission (Youssefi et al., 2022). Therefore, we utilize the monthly PERSIANN-CDR dataset from 2017 to 2023 to identify rainy periods for analysis. Moreover, the months that had the average temperature in the suitable range for the growth of *Anopheles* mosquito were extracted. Finally, by analyzing precipitation and temperature data from 2017 to 2023, we identify optimal periods for the growth and survival of *Anopheles* mosquitoes and use images from these periods for the water extraction model.

3.3.2 Water body extraction model: After determining the study period, acquiring Sentinel-1 images is necessary. Multitemporal data improves the ability to detect temporary water bodies and reduces speckle noise. Also, instead of directly using time series images, median operator was implemented for temporal aggregation. After acquiring images, SWI index was applied on the images and water bodies were extracted.

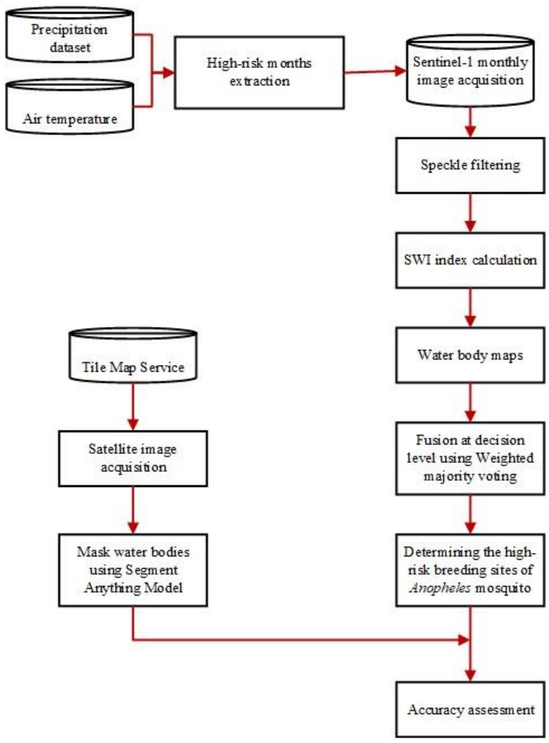

Figure 2. Proposed workflow.

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3.3.3 Detection of high-risk breeding sites of *Anopheles* mosquito: After calculating the SWI index and extracting monthly water bodies over seven years (2017-2023), water body maps were generated. Then, these maps were fused at the decision level using weighted majority voting to identify high-risk areas. These areas provide the surface water necessary for the growth and development of *Anopheles* mosquitoes. To assign weights, we use the monthly precipitation levels to influence the voting process. Precipitation levels, which indicate both sensitivity and specificity, serve as a relevant measure of algorithm performance. This enhances the impact of decisions with high sensitivity and specificity. The weights are calculated by dividing each month's precipitation value by the sum of all monthly precipitation values.

3.3.4 Accuracy assessment: To identify water bodies, center of 260 water bodies were first marked in Google Earth Pro as points and subsequently exported as a shapefile. These points were chosen based on visual interpretation, with many representing depressions that accumulate water during the rainy season. In contrast, during the dry season, these depressions display distinct characteristics due to their silty clayey bed texture, which results from soil erosion caused by runoff, as confirmed by field assessments. Field observations were conducted on 31 of these 260 depressions.

The satellite image was prepared for segmentation by downloading tiles and assembling large georeferenced images using Tile Map Service. The SAM model path was defined, and SamGeo was initialized with the specified parameters. The model type is specified as "ViT_H". The checkpoint file associated with this model is "sam_vit_h_4b8939.pth". The automatic setting is set to "False", indicating that automatic mode is disabled. Finally, the "sam_kwargs" parameter is set to "None", implying that no additional keyword arguments are provided for the model's configuration. The shapefile was then converted from a geodata frame to a list of point coordinates. Each point was predicted, segmented, and saved into a separate geotiff mask by iterating over the list of coordinates, creating a unique mask for each point. All masks were then resampled to a 10m resolution, matching the Sentinel-1 resolution, and merged into a single file as a mosaic mask.

To assess the accuracy of extracted high-risk sites from the proposed method, SAM-generated masks for 260 water depressions were used. Additionally, 260 non-water area samples were randomly selected using Google Earth Pro. The model's performance was evaluated using a confusion matrix (Table 1) and comprehensive indicators including Precision, Recall, F1-score, Overall Accuracy (OA), and Kappa.

	Water	Non-Water
Water	TP	FN
Non-Water	FP	TN

Table 1. Confusion matrix for water body detection

Also, in another evaluation, the results of the proposed method will be compared with the results of machine learning classifiers.

4. Results

4.1 Extraction of high-risk periods

The graphs of monthly precipitation and monthly mean temperature in seven weather stations are shown in Figure 3 and Figure 4.

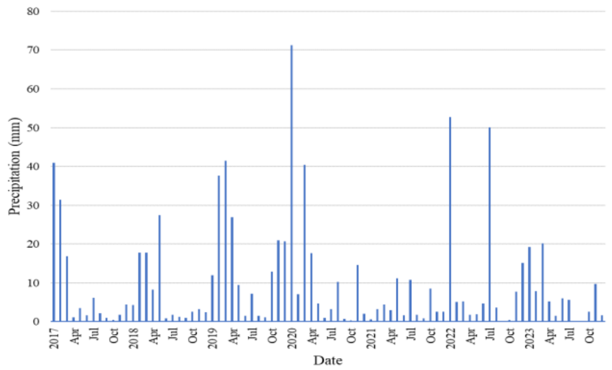

Figure 3. Monthly precipitation.

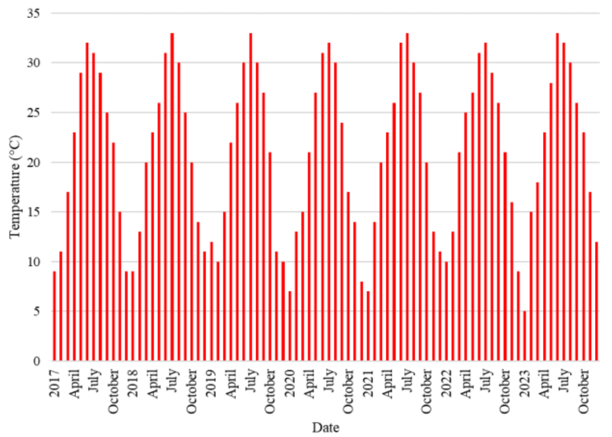

Figure 4. Monthly mean temperature.

Finally, by aggregating the results of monthly precipitation and monthly mean temperature, we investigated the trend in the contribution of each month to annual precipitation and temperature. According to the results in most years, in the months of March, April, May and July, in terms of both precipitation and temperature, conditions were favorable for the formation of *Anopheles* mosquito larval habitats.

4.2 Water body extraction model

The SWI index was applied on Sentinel-1 images for the selected study period from 2017 to 2023. Figure 5 shows the detected water bodies at 10-m spatial resolution over a tiny area inside the study area for selected four months of 2023.

Visual assessment clearly shows that this approach effectively delineates water areas, highlighting depressions with a high potential for water retention. Identifying these areas relies on the storage capacity of the depressions and the volume of water they hold, which are influenced by the dimensions of the depressions, the slope of the region, and their connectivity through waterways. The index also reveals fine details due to its high spatial resolution. By comparing water maps from different months, changes in surface water coverage can be observed, which could be attributed to variations in precipitation, evaporation, and infiltration.

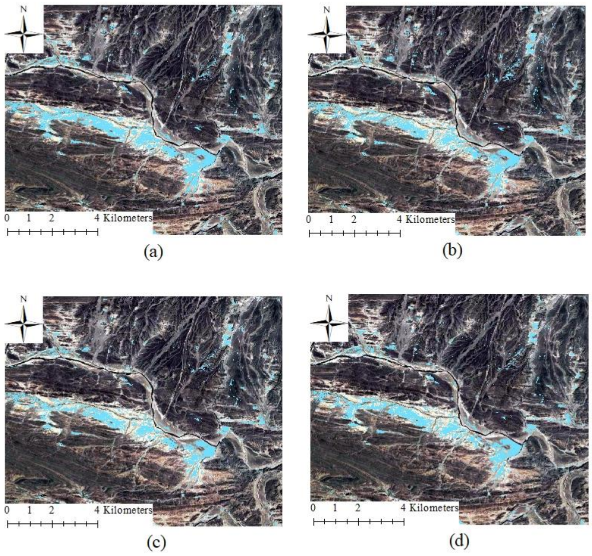

Figure 5. Maps of extracted water bodies using SWI index during the study period for a tiny part in the study area in 2023: (a) March, (b) April, (c) May, and (d) July.

4.3 Detection of high-risk breeding sites of *Anopheles* mosquito

As mentioned earlier, depressions with possibility of water accumulation during high-risk times of the year, have the potential to become the habitat of *Anopheles* mosquito larvae. Therefore, all 28 classification maps as for four months in seven years of study are considered. For this purpose, weighted majority voting is utilized, so that weights are calculated based on the amount of precipitation. The output map of this analysis will be used for accuracy evaluation. Results of this analysis for a tiny part of study area is shown in Figure 6. Areas delineated in blue color indicate depressions held water which was obtained using a decision fusion rule on the results of 28 months of study.

Figure 6. High-risk areas of *Anopheles* breeding sites for a tiny part in the study area.

4.4 Accuracy assessment

By performing SAM on marked points represented high potential areas for *Anopheles* breeding habitats, 260 masks were generated using point-based approach. By focusing on a singular point, SAM was able to provide precise segmentation results. Result of masking a sample depression is shown in Figure 7.

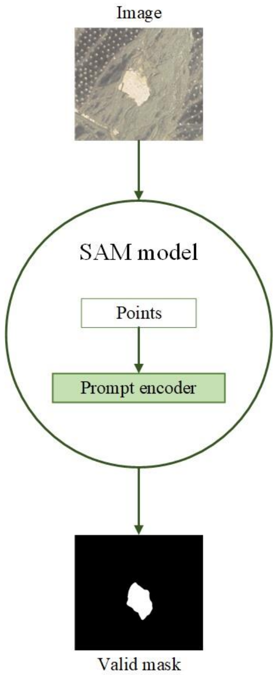

Figure 7. A sample of masked depression using SAM.

To accurately validate the proposed methodology, and provide meaningful and reliable quantitative analysis of the final map, masks generated from SAM model and sample points of non-water body areas were overlaid on the output map of weighted majority voting method. Then the confusion matrix was obtained by comparing the predicted results and the reference masks. The results are shown in Table 2.

Evaluation measure	Value
Precision	98.7%
Recall	93.4%
F-1 score	96%
OA	96.1%
Kappa	92.2%

Table 2. Accuracy of the proposed method

As an alternative method, the results of this presented method have been compared with the results of machine learning methods. For this purpose, using two classifiers of Random Forest (RF) and Support Vector Machine (SVM), a land-cover classification with 4 classes has been done, one of those classes is the areas that have the possibility of water retention and habitat formation. The results of these classifications are shown in Table 3:

Evaluation measure	RF	SVM
Precision	79.6%	74.6%
Recall	100%	97%
F-1 score	88.6%	84.7%
OA	96.1%	86.9%
Kappa	78%	73.8%

Table 3. Accuracy of machine learning models

The model's high precision and recall highlight its effectiveness in accurately identifying water bodies. This balance minimizes false positives, which is essential for reliable water resource monitoring. The high F1 score further confirms the model's robust overall performance, with an overall accuracy of 96.1%

and a kappa coefficient of 92.2%. Key factors contributing to this success include the suitability of Sentinel-1 imagery for distinguishing water bodies from other land covers and the robustness of the proposed method. Additionally, object-based evaluation and the model's ability to adapt to temporal changes in water dynamics enhance its performance. Additionally, by comparing Table 2 and Table 3, unlike machine learning models with lower accuracy, our approach is a flexible and efficient solution for detecting water across extensive study areas, contributing to advancements in identifying *Anopheles* mosquito larvae habitats.

5. Conclusion

In the last two decades, the use of remote sensing for the control and prevention of diseases, including malaria, has become widespread. This paper presents a model to map high-risk water bodies as prone habitats of *Anopheles* mosquito larvae through monthly aggregated medium spatial resolution Sentinel-1 imagery with considering temperature and precipitation elements of environmental parameters and employing weighted majority voting. The results indicated that the approach performed well in detection of water bodies with high risk of *Anopheles* larvae habitat formation. Since it is not easy to provide suitable features and sufficient training data, in the absence of classification machine learning models, this model overcomes the challenges associated with insufficient training data by providing a flexible way to accelerate the efficiency of water detection areas, so as to facilitate high-risk *Anopheles* habitats detection and monitoring in a large study area. This methodology stands as a valuable tool for detecting potential *Anopheles* mosquito habitats, especially in regions at high risk for vector-borne diseases. Our research outputs are able to support public health officials to control and predict malaria spread over extensive areas and finally the risk map can be beneficial for public warning and awareness.

Acknowledgements

The authors would like to thank the Tehran University of Medical Sciences (TUMS) for providing financial support. Also, they are very grateful to the Department of Health of Saravan City for contributing to providing field information from the study area. They would also like to thank the Iran Meteorological Organization (IMO) for providing the meteorological data.

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