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RESEARCH ARTICLE

Influence of Environmental Factors on the Mosquito Vector Habitat Distribution in Urban Areas of Faisalabad, Punjab

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Abstract The viruses that cause malaria, Dengue hemorrhagic fever, and Rift Valley fever are primarily spread by mosquitoes. Globally, mosquito-borne diseases pose a serious threat to public health, particularly in crowded cities. The goal of the current study was to update knowledge about the mosquito (Diptera: Culicidae) fauna of Punjab region, Pakistan's District Faisalabad, and forecast the distribution of the larvae of the most important mosquito vectors in this area. Environmental factors such as water sources, land use, temperature, and humidity were recorded at each collection location. A perspective for the geographic distribution of dengue vectors in the metropolitan areas of Faisalabad was created using GIS-based spatial analytic tools after the data was gathered. The number of mosquito larvae was assessed in connection with the physiochemical characteristics (pH & TDS) of breeding grounds. Mosquito larvae were collected from January 2024 until December 2024. *Aedes aegypti* was the most important vector discovered in Faisalabad. To predict the species distribution of *Aedes aegypti* in the district of Faisalabad, 19 bioclimatic variables were combined with the data from the collection. More than 100 locations yielded more than 1800 mosquito larvae. The northeastern region of the Faisalabad district was identified as having the best suited lands. The region that was least conducive to the presence of *Aedes aegypti* was the southwest. Precipitation factor (bio8) contributed the most in the presence of this vector, accounting for over 40%, followed by bio19, which contributed 20%.

Keywords: Mosquito vectors, spatial distribution, GIS, dengue, *Aedes aguptii*, urban areas, Faisalabad, Punjab, Pakistan.

Introduction

Mosquito-borne diseases are a growing concern in many urban areas, especially in developing countries like Pakistan. In cities such as Faisalabad, rapid urban growth, poor drainage, stagnant water, and changing weather conditions create ideal breeding grounds for mosquitoes. Factors like temperature, humidity, rainfall, vegetation, and land use play a key role in shaping where mosquitoes can live and thrive. This study aims to explore how these environmental elements influence mosquito habitats across different parts of Faisalabad. Using mapping tools and ecological models, the research will help identify areas at greater risk, ultimately supporting more focused and effective mosquito control and public health strategies.

Due to the change in the climate, urbanization and human activities, Pakistan has to deal with high risk of mosquitoborne illnesses in last few years. In disease transmission, researches from region such as Peshawar and Punjab have highlighted the role of *Aedes* mosquitoes, particularly *Ae. aegypti* and *Ae. albopictus*. Research indicates that these species differ in bacterial diversity and *Wolbachia* infection, with *Ae. albopictus* hosting more diverse strains. Environmental surveys have recognized parks,

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forests, and scrapyards as key breeding grounds, with mosquito diversity peaking during the rainy season. Advanced tools like GIS and AHP have also been used to map high-risk areas and assess environmental factors. These insights support integrated, targeted mosquito control strategies by combining ecological, microbial, and spatial data.

Ammar et al. (2025), discovered that due to climatic changes in Pakistan, deforestation, urbanization and poor sanitation causes the arboviral diseases at high level. As there is no proper investigation system in Pakistan, it causes the great hurdle in the way effectively tracking the disease prevalence. High prevalence rate of dengue, West Nile virus, chikungunya, and Japanese encephalitis have caused the major health issues along with other hidden arboviral diseases. So improved investigation system, research and control strategies are required to overcome these challenges.

Nayab et al. (2025), completed the research work by focusing on Ae. aegypti and *Ae. albopictus*. Mosquitoes that were collected using Gravitraps, and their species were confirmed through molecular methods, these investigations have pointed out the presence of Wolbachia in Aedes mosquitoes, in Peshawar, the northwest region of Pakistan. With *Ae. albopictus* hosting 921 bacterial species, while *Ae. aegypti* had only 239 species, the 16S rRNA sequencing disclosed remarkable differences in bacterial diversity, Both species were found to carry Wolbachia, with Ae. aegypti infected with Wolbachia pipientis, and Ae. albopictus showing a co-infection of two Wolbachia strains, Wolbachia pipientis and Wolbachia bourtzisii. To control dengue and other mosquito-borne diseases in the area, these researches pointed out the significance for using Wolbachia.

Mehmood et al. (2024), found that, based on behavioral and feeding habit, mosquito species show the great degree of variations in habitat selection. By analyzing microhabitats, species diversity, and habitat web structures through the surveys conducted in the Chakwal district of Punjab, Pakistan, identified the potential mosquito's habitats. A total of 580 mosquito specimens were collected, representing 12 species from five genera. Crop fields had the lowest while parks, forest areas, and scrapyards had the highest mosquito populations. Parks also emerged as the most species-rich habitats, with graveyards showing the least diversity.

Ullah et al. (2023) explored that Mosquito distribution across different agro-ecological zones of Punjab is shaped by seasonal changes, land use, and human activity, all of which influence disease risk. Surveillance was conducted in six zones, collecting samples from stagnant water sources during various seasons. A total of 24 mosquito species were identified, with higher diversity observed during the rainy season. Anopheline mosquitoes were found across both rural and urban areas, while Aedine species were mostly limited to northern irrigated plains, especially around Changa Manga Forest. Culicine mosquitoes were widespread and present year-round. Some species showed specific habitat preferences, such as *C. crassipes* in rainfed areas and *M. chamberlaini* in both urban and rural environments.

Climatic factors significantly influence the presence of *Aedes aegypti* larvae in indoor and outdoor water containers across various districts. Analysis showed a strong link between weather patterns and larval abundance, except in Faisalabad during the summer, where no significant association was found. Containers containing stagnant water placed at specific places also played a significant role in this purpose. These researches provided the remarkable understandings and demonstrations about potential breeding sites of mosquitoes and manipulating the crucial mosquitoes control strategies (Malik et al., 2023).

In 2019, Ali and Ahmed, provided a detailed map that represents the complete sketch of diseases caused by mosquitoes in Kolkata Municipal Corporation, with the help of geographical information system (GIS) and analytical hierarchy technique. To recognize the weightage of chosen items, a pairwise contrasting matrix, a choice-based classifying technique was formulated.

Jemal and Thukair (2018), illustrated that a pairwise comparison matrix was used to assess the weights of ten pertinent environmental components. A geo-database was also created using the weight of each causal element to facilitate overlay analysis. To confirm the significance-measurement and decision-making processes, the consistency ratio was created. Because it is less than 0.1, the compatibility ratio to the select variables, which was determined to be 0.0470, is considered accurate. The study's analysis shows that a number of important factors.

The current study demonstrates the extensive applicability of satellite data and a spatial approach to the zonation of epidemic diseases. Numerous studies across the globe have highlighted the effectiveness of Geographic Information Systems (GIS) and environmental modeling tools in understanding mosquito vector distribution. For instance, research conducted in the Eastern Province of Saudi Arabia used GIS and meteorological data to map mosquito breeding sites, revealing that temperature, humidity, and rainfall play key roles in mosquito abundance. Similar work in Hawaii emphasized the need to include environmental variation—such as rainfall and temperature thresholds—when predicting mosquito habitats, especially in areas with high population density. In Virginia, USA, GIS was used alongside remote sensing and field data to forecast the abundance of mosquito species, showing how environmental factors could guide risk assessments and disease surveillance.

Meanwhile, in Pakistan, although species distribution modeling (SDM) has been used to study mosquitoes, GIS-based studies remain limited. Past outbreaks like the 2017 dengue epidemic in Khyber Pakhtunkhwa highlight the urgent need for spatial modeling. Studies using techniques such as binary logistic drift and binomial kriging have shown promising results in identifying high-risk areas. Traditional mosquito control methods, such as chemical pesticides, have been challenged by rising resistance in mosquito populations, making ecological modeling even more critical.

Materials and Methods

Description of the study area

Pakistan's terrain is defined by a number of regions, including the Indus Plain, the Northern and North-Western Mountains, the Potwar Plateau, the Balochistan Plateau, and Salt Range, and other ecosystems and climate zones. Faisalabad, Pakistan, is a 3.4 million-person city that occupies 3,358 km2 in northeastern Pakistan, situated between the Ravi and Chenab river plains. According to Saleem and Mahmood (2023), the southern half is estimated to be bordered by Sahiwal and Toba Tek Singh, the northern extremity by Chiniot and Hafizabad, Nankana Sahib to the east, and Jhang to the west.

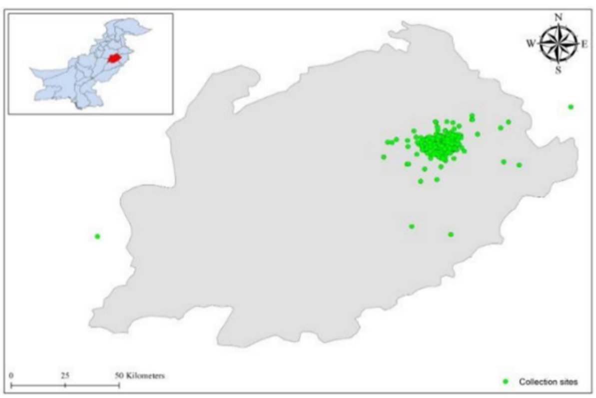

Figure 1. Pakistan map showing collection sites in Faisalabad.3.2.

Data Collection

Field trips and surveillance operations were carried out to collect mosquito larvae. After sampling every breeding location, the most usual and promising habitats were chosen from both lower and higher elevations. From January 2024 to December 2024, the collection of mosquito larvae was conducted continuously. To collect mosquito larvae, a regular 350 ml plastic dipper was utilized. By using a global positioning system unit (GPS), the coordinates of the collection sites were acquired (Garmin, eTrix). Each recovered mosquito larva was identified and submerged in 80% alcohol.

Diverse Breeding Habitats:

Various breeding sites were surveyed for mosquito larvae collection, including streams, wells, water containers, and pools. Here are some images depicting these sites.

Figure 2. Mosquito larvae emerged in the stagnant water present in a tree aperture, Jinnah colony, Faisalabad district.

Figure 3. *Rainwater accumulation in a park of Chak Jhumra, Faisalabad district.*

Identification of Mosquito

Larvae were gathered from several nesting locations using conventional dipping methods in order to identify mosquito species. They were then raised in a controlled laboratory environment until they matured into adult mosquitoes. Morphological keys and taxonomic guides were then used to identify the emerging adults down to the species level (Rueda, 2004; Gillies & Coetzee, 1987). Important morphological traits such wing venation, leg banding patterns, and abdominal markings were used for identification.

Morphological identification is still a valid way to distinguish between mosquito species, especially in field-based research, according to Alahmed et al. (2011). Their study acknowledged that environmental influences can affect morphological changes, but it also emphasized the significance of defined taxonomic keys for precise species confirmation. In order to ensure correctness, we used published taxonomic keys and expert assistance to crossverify our identification method. For use in MaxEnt, Dengue mosquitos were recognized and data was monitored in CSV (Comma separated value) format.

Physiochemical characteristics

The pH and total dissolved solids of every breeding locations were analyzed through the pH meters along with TDS (HANNA Instruments, USA).

Visualisation and analysis

The result of molecular docking was analysed using different software such as AutoDock 4.2, PyMOL and LigPlot program. PyMOL program was mainly used for visualisation of the structures. The main parameters for molecular docking analysis were the binding energy values of the protein-ligand interaction, hydrophobic interaction and the number of hydrogen bond formation. The binding energy value for each compound was shown as a result of molecular docking and the best interacting compound of both enzymes was selected. Besides, the number of hydrogen bonds formation and the residues that formed the hydrogen bonds with the ligand were identified using AutoDock 4.2 software. The distance of hydrogen bonding between the ligand and the interacting residue was being calculated using PyMOL. Also, AutoDock 4.2 software was used to reveal all the interacting residues of the protein, and each ligand; meanwhile, Ligplot software was used to visualise the hydrophobic interaction of the protein and the ligands.

Modeling procedures

Accurate test statistics and independent evaluating data is required due to the nichebased nature of the distributional models. In order to offer distinct test data, the Faisalabad district was selected for the collecting of mosquito larvae kinds from multiple grid cells. Test statistics were then acquired using Maxent software. To describe the environment of mosquito larvae, 19 bioclimatic layers temperature layers and According to Phillips et al. (2006), from the WorldClim database version 1.4 (www.worldclim.org) eight precipitation levels were taken. 30 arc-seconds (1 km) is spatial resolution of these bioclimatic strata. After being shrunk to the size of the Faisalabad district, in ASCII grid format each of these bioclimatic layers was recorded so that MaxEnt could use it. The model builder tool in ArcGIS version 10 was used to reduce these layers. The geographical distribution of the species was modeled using MaxEnt software version 3.3. The program was set up using the "Auto features" option, ASCII output file format, and logical output structure as recommended by Phillips and Dudík (2008).The Maxent software connected predictor characteristics (environmental and topographical) with the distribution of target potential species.

The value assigned to any pixel is = (The probabilities of that pixel + probabilities of all other pixels having equal or lower probability values) X 100

Any pixel with a value of 100 indicates the most adaptability to depict the presence of the species, while a value of 0 indicates the least compatibility (Phillips et al., 2004; Phillips et al., 2006).

Evaluation Metrics

MaxEnt

Maximum Entropy (MaxEnt) originated in statistical mechanics (Jaynes, 1957). It is a common method for predicting topographical dispersion of mosquitoes in the research area. Only presence data and ecological data are required for MaxEnt to simulate species distribution (Phillips et al., 2006). In a large-scale model discrimination investigation, Maxent performed well (Elith et al., 2006). Similarly, the analysis of four species distribution modeling approaches revealed that, even with a small sample size, maxent could produce extremely valuable and accurate results (Hernandez et al., 2006).

The model developed using this approach also shows how climate change impacts the habitat of the target species (Phillips et al., 2004; Hernandez et al., 2006). Only a little number of specimens can be employed for the species compatibility referred by maximum (Pearson et al., 2007; Ortega and Townsend, 2008; Wisz et al., 2008; Kija et al., 2013). Even with sample numbers as little as five, Maxent has proven to have a high success rate (Pearson et al., 2007).

The Genetic Algorithm for Rule-set Production (GARP) performs worse than maxent for sample sizes smaller than 10 (Pearson et al., 2007). The marginal density along the study area region contrasted to the conditional density at the presence sites of predictors to forecast species-suitable habitats using maxent (Conley et al., 2014). Maxent can generate species distribution models using five occurrence tracks (Hernandez et al., 2006). In any event, for a reliable forecast, at least 30 recurrence data should be present (Wisz et al., 2008). Models produced by Maxent show less omission errors than those produced by GARP (Foley et al., 2010).

Determining the importance of variables in model building

The relative importance and value of each variable in the geographic distribution of species models are analyzed by Maxent using the Jackknife technique. By the Jackknife test, three different model types are produced (Phillips et al., 2006; Phillips and Dudik, 2008):

- Models created with all but one variable considered.
- Models created with one variable and all other variables eliminated at the same time.
- Models that contained all of the variables.

The initial learning gain increases when the model is developed with only one variable, while decreases as the most important variable is eliminated from the model, but. In other words, the least AUC values shown by variables that are eliminated from the model show, while the largest AUC values by variables that are added individually (Phillips et al., 2006). In order to analyze the prediction accuracy, Maxent automatically divides our mosquito sample information into training and test sets. Both threshold-independent and threshold-dependent methods are used to evaluate how accurate the model predictions are (Phillips et al., 2006). The threshold independent approach uses external omission rate (the percentage of test sites that fall in pixels that are not suitable for the species) and proportional projected area (the percentage of all pixels that are favorable for the species) to evaluate the model prediction. Despite the fact that independent threshold assessments utilize the recipient's operational features to measure the area under the curve.

Receiver Operating Characteristics Curves (ROC)

Maxent's performance is indicated by the area under the curve (AUC) value, which is typically the unit square section of the area with a value between 0 and 1. Using this receiver operating feature approach, Maxent predicts the distribution according to species (Fawcett, 2006). This curve shows how well a classifier works when a threshold parameter affects its output. This graph shows the ratio of true and false positive values for each level. The classifier has classifies a faction "x" of negative examples (grids without occurrence localities) as positive and a proportion "y" of positive cases as positive shown by some location on the graph (Phillips, 2004). The points on the graph are joined to create a curve. However, the area under the curve (AUC) shows how likely it is that the classifier will correctly arrange the two points (Phillips, 2004). An AUC value of less than one indicates a good classifier. (Wiley and others, 2003). Threshold unbiased measurements show sensitivity and specificity on a graph. Sensitivity is the accurately true positive predicted sites for a species, while selectivity is the real, exactly determined negative sites (Fielding and Bell, 1997; Phillips et al., 2006; Phillips and Dudik, 2008). The AUC value can be computed by the differential capacity of the model. 0.5 to 0.7, 0.7 to 0.9, or > 0.9 and 1.0 are AUC values of the model's low, fair, high, and perfect discriminative power correspondingly (Brooker et al., 2001; Phillips et al., 2006; Phillips and Dudik, 2008).

Results and Discussion

In species distribution modeling (SDM), visual tools such as response curves and the jackknife test play a vital role in exploring how environmental factors shape the presence or spread of a species. Response curves visually depict the influence of individual environmental variables on species predictions, helping researchers understand which factors are most critical and which have limited impact. Interpreting these curves, however, can be challenging when variables are closely related, as overlapping effects may obscure clear patterns. Alongside these, the jackknife test serves as a powerful method to evaluate the model's reliability by systematically excluding variables or data points to observe changes in prediction accuracy. This process highlights potential overfitting and helps determine how well the model can handle unseen data. Together, these methods provide a clearer picture of ecological relationships and support efforts in species conservation and environmental planning.

Results

Mosquito distribution in Faisalabad

Larvae of *Aedes* were collected from different sites in Faisalabad city. Table discusses their websites in more detail.

Analysis of omission/commission

The forecasted area and exclusion ratio are shown against the progressive approach in the following figure. The original presence records and, if test data is used, the test records as well are used to evaluate the exclusion ratio. For this reason the specification of the progressive approach, the exclusion ratio must be around the predicted omission.

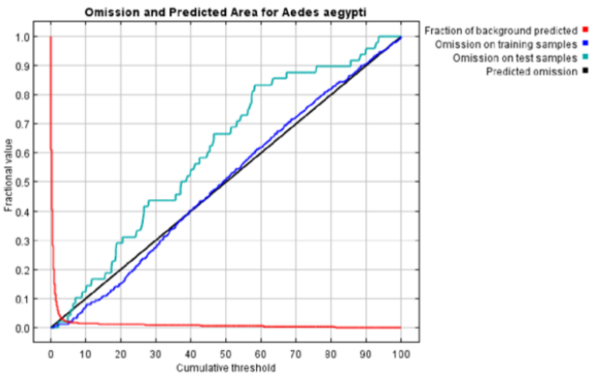

Figure 4. *Omission and predicted are for Aedes aegypti*

In the following figure the receiver operating characteristic (ROC) curve for the similar data is shown. Keep in mind that specificity is determined by expected area rather than actual commission; see the Phillips, Anderson, and Schapire study area to understand about its, on the support page. This suggests that the highest AUC that may be attained is less than 1. The maximum test AUC that could be achieved if test data were taken from the Maxent distribution itself would be 0.986 instead of 1, even if the test AUC may be greater.

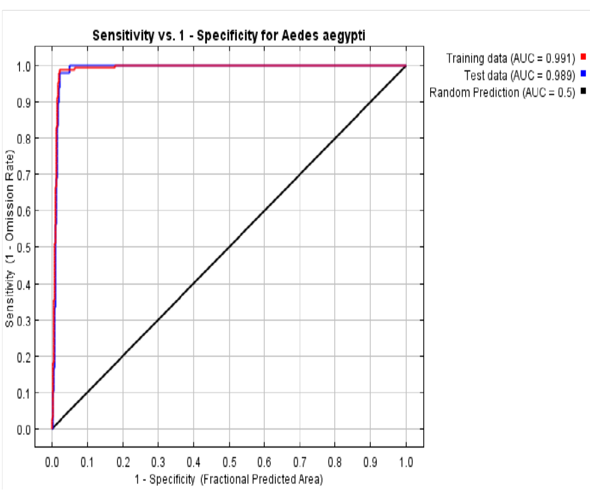

Figure 5. *Sensitivity vs. 1-Specificity foe Aedes aegypti*

Below is a list of some specific criteria along with the corresponding exclusion ratios. When test information is provided, if there are less than 25 test samples ,binomial chances are computed appropriately; if not, a conventional method to the binomial is used. The null hypothesis, which states that test sites can be expected no more accurately than by a random prediction with the same fractional anticipated area, is supported by these one-sided p-values. The total of the following is reduced by the "Balance" threshold: Six * fractional predicted area +.04 * cumulative threshold + 1.6 * training omission rate.

Table 2. *Maxent modeling analysis of Aedes aegypti and its output.*

Cumulative threshold	Logistic threshold	Description	Fractional Predicted area	Training omission rate	Test omission rate	P-value
1.000	0.001	Fixed cumulative value 1	0.169	0.007	0.000	1.42E-53
5.000	0.085	Fixed cumulative value 5	0.021	0.014	0.042	0E0
10.000	0.313	Fixed cumulative value 10	0.016	0.075	0.125	0E0
0.967	0.001	Minimum training presence	0.176	0.000	0.000	3.849 E-51
13.773	0.430	10 percentile training presence	0.014	0.095	0.167	0E0
5.470	0.106	Equal training sensitivity and specificity	0.020	0.020	0.042	0E0
5.004	0.085	Maximum training sensitivity plus specificity	0.021	0.014	0.042	0E0
4.855	0.079	Equal test sensitivity and specificity	0.022	0.014	0.021	0E0
4.855	0.079	Maximum test sensitivity plus specificity	0.022	0.014	0.021	0E0
1.997	0.004	Balance training omission, predicted area and threshold value	0.063	0.007	0.000	0E0
4.256	0.057	Equate entropy of thresholded and original distributions	0.024	0.014	0.021	0E0

Response curves

In these graphs the effect of every environmental variable on the Maxent forecast is shown. When each environmental factor is changed while maintaining a fixed mean sampling value for all other environmental variables, the graphs illustrate how logistical prediction varies. It perhaps be demanding to clarify the curves if the variables that you employ are closely related since the model could rely on the correlations in ways that are not shown in the curves. In other words, the curves demonstrate the minimal effect of changing a single variable, even when the model could advantageous from changing groups of variables collectively.

Molecular Docking Analysis of DPP-4 Enzyme with Polyphenol Compounds

Similar to AG enzyme, all the selected polyphenol compounds and sitagliptin were successfully docked at the targeted binding sites of the DPP-4 enzyme. The results of the molecular docking for each combination that formed a complex with DPP-4 enzyme were summarized in Table 3 with their corresponding binding energy values. In Table 4, it stated the results of the hydrogen bond formation and the interacting residues of DPP-4 with each polyphenol compound and sitagliptin.

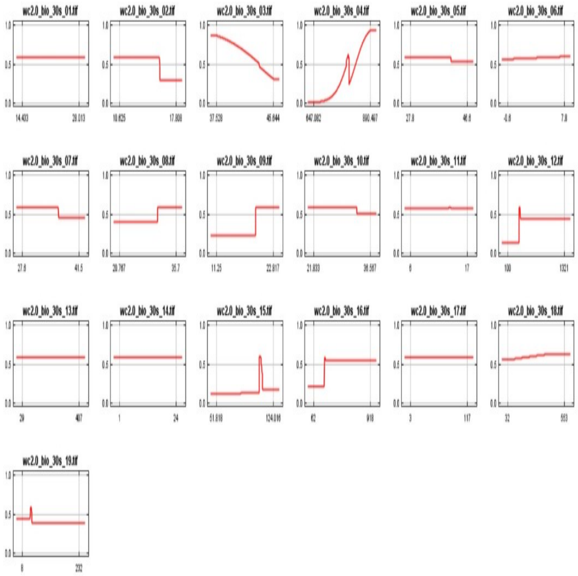

Figure 6. *Responsive curves in accordance to each environmental variable.*

Every following curves represents a different model, compared to the marginal response curves above, i.e., a Maxent model developed using just related variable. The graphs show the weakness of forecasted appropriateness on the variable of choice and weaknesses resulting from association between other factors and the variable of choice. If there are strong relationships between them, the variables may be simple to comprehend.

Table 3. *Estimate for the Relative Contributions of Ecological Factors.*

Variable	Percent contribution	Permutation importance
wc2.0_bio_30s_15.tif	19.9	5.7
wc2.0_bio_30s_16.tif	18.4	12.6
wc2.0_bio_30s_12.tif	11.3	22.1
wc2.0_bio_30s_19.tif	9.8	0
wc2.0_bio_30s_09.tif	9.6	24.1
wc2.0_bio_30s_08.tif	8.6	0.7
wc2.0_bio_30s_03.tif	7.1	7.1
wc2.0_bio_30s_02.tif	5.1	7.2
wc2.0_bio_30s_07.tif	4.6	0
wc2.0_bio_30s_10.tif	3.8	0
wc2.0_bio_30s_04.tif	1.7	20.4
wc2.0_bio_30s_05.tif	0.1	0
wc2.0_bio_30s_18.tif	0	0
wc2.0_bio_30s_13.tif	0	0
wc2.0_bio_30s_11.tif	0	0.2
wc2.0_bio_30s_06.tif	0	0
wc2.0_bio_30s_17.tif	0	0
wc2.0_bio_30s_14.tif	0	0
wc2.0_bio_30s_01.tif	0	0

The Jackknife test of constant relevancy findings are shown in the following image. Since it has the most benefit when utilized alone, the ecological factor wc2.0_bio_30s_12.tif seems to contain the most valuable information. Since Wc2.0_bio_30s_15.tif is the component of the environment when deleted, decreases the gain the most, it looks like to have the most of data that is absent in the other variables.

Analysis of variable contributions:

The given table presents predictions about comparative contribution made by environmental factors to the Maxent model. In each training process iteration, the initial estimate is computed by adding the addition of the established gain to the related variable's contributions, or its removal in the event that fluctuate the true worth of lambda is negative. The learning presence and background data of every single environmental component are permuted at random for the second evaluation. The training AUC drop resulting from reevaluating the prediction model on the permuted data is shown in the table, adjusted to percentages. When the variables that predict are connected, variable contributors should be carefully evaluated, much as the variable jackknife

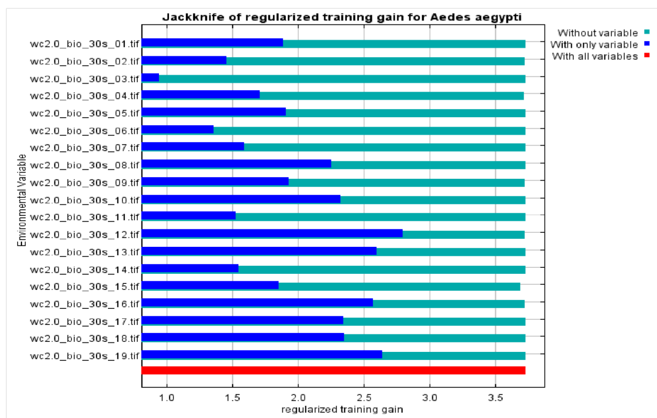

Figure 6. *Jackknife of regularised training gain for Aedes aegypti.*

In the following picture the identical Jackknife test is shown, but test gain is used in place of training gain. Keep in mind that test findings may cause us to change our minds about which aspects are most crucial.

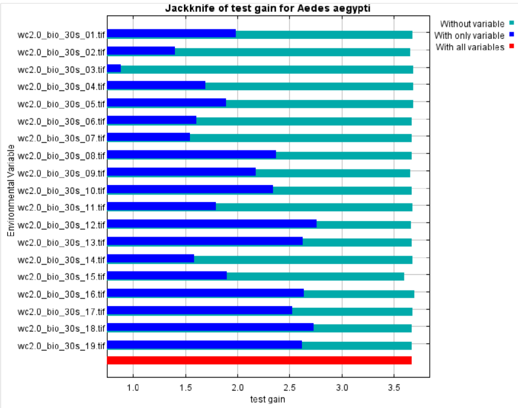

Figure 7. *Jackknife of test gain for Aedes aegypti*

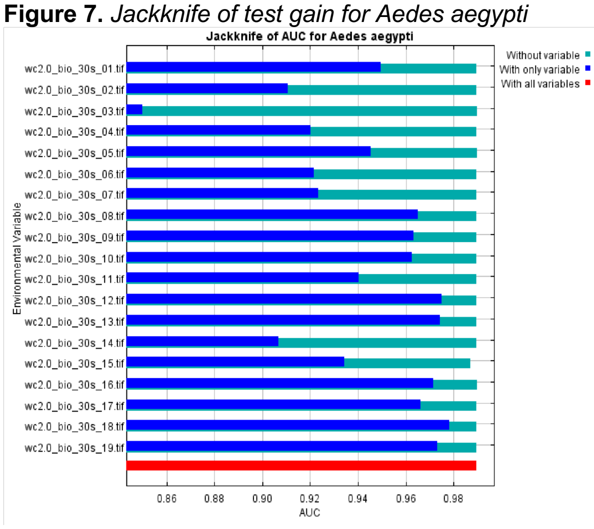

Figure 8. *Jackknife of AUC gain for Aedes aegypti*

Discussion

The graphics that are displayed shed light on a critical aspect of species distribution modeling (SDM) by emphasizing reaction curves and the understanding of Maxent models. These visualization approaches are essential for comprehending how environmental conditions impact the projected distribution of species.

Response curves must be understood in order to comprehend the relationship between environmental conditions and species dispersion forecasts. By examining these response curves, we can ascertain the extent to which changes in a particular environmental variable impact a species' predicted distribution. Interpreting response curves is crucial to understanding the ecological interactions between species and their environments. If a response curve for a specific environmental variable is generally flat through most of range of values, it may not have a powerful effect on distribution of species. In particular, the presence of significant correlations between environmental variables also entangled the interpretation. In this scenario the model may manipulate connections between factors in such ways that response curves do not readily show. Contrastingly to the marginal reaction curves which were addressed previously, these graphs describe how the selected variables expected to appropriately affects selected variables along with the other factors to produce dependencies. The graphs is in depth visually describe how the change of environmental circumstances impact the expected expansion of species. These graphs enable the researchers to understand the pattern of ecological processes in controlling specie distribution.

Concluding that response curves along with Maxent model response curves are the most crucial tools used by researchers to develop relationship between environmental factors on species distribution, how they understand species distribution. This research graphs are a quick way to understand the ecological dynamics which are effecting species distribution and steps can be taken to conserve species and managing the environmental conditions to the extent they can.

The jackknife test is as essential tool as the previously described response curve and Maxent model response are used for the SDM (species distribution modeling). Jackknife test is a resampling method used to determine the statistical estimator's variance and bias. After understanding model on all the other data points, this cross-validation is called leave-one-out, and it is used to test the model on excluded data point. In this process the test is repeated for each data point in the dataset. The jackknife testis used to draw graphs that depicts the Maxent models performance and it's stability in that particular research. By comparing actual and expected values of every missing data point research can evaluate the accuracy of models' predictions. The jackknife test helps in identifying over fitting model by evaluating the model's performance on imagined data points. If prediction across all the data points came out consistent then it model appears to be stable and suitable for handling unknown data. Over fitting, are the model's where new data effect the model's ability to detect its target. If the jackknife test predictions are unlike from the training data predictions than this is over fitting model.

Conclusions

The study provides valuable information about the geographic dispersal region for the important mosquito species that act as vector represent a major health risk. To prevent the spread of illness, selected vector management measures are necessary. The predictive models developed in this work can help direct efforts to manage vectors in the regionof vector mosquitoes in the urban regions of Pakistan especially Faisalabad, using GIS techniques. Since the area is main suitable breeding.

There are various restrictions on this study. Because of the district's terrain in some places, mosquito captures from the allocated locations were insufficient for field validations of these models. Finding high-risk areas close to water sources and mosquito populations was one way to deal with this problem. Positive results were occasionally achieved, even though these efforts were not always successful. In particular, accessibility was a major obstacle to the collection of Ae. aegypti from high-risk areas; just two sites produced positive results, and the rest sites produced negative results because of a lack of water or logistical challenges in getting to them. However, our findings are supported by the two positive locations in high-risk zones, which validate our model predictions.

In Faisalabad, the region of Punjab in Pakistan ,there is spread of diseases affecting its urban areas these diseases are carried by mosquitoes, so some targeted vector control measures are needed to put in that place. Moreover it is needed to analyze the directional proficiency of mosquito species at different places. So in order to check the vector potential and dispersion in metropolis of Faisalabad, Punjab, Pakistan there is need of more larvae collection of mosquito. There are some strategies we can adopt to control this disease spreading by vector by different controlling strategies that includes use of pesticide spray, source reduction of larvae, reduction of mosquito breeding grounds , control of mosquito population , improvement of sanitary conditions, improvement of waste management infrastructure, implementation of IVM(integrated vector management) as it contain a number of control mechanism , public awareness about the causative agents of diseases , carry out a range of mosquito control programs with the help of environmental departments etc.

Author Contributions

S.S: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. M.R. and M.N.: Writing – review & editing, Visualization, Formal analysis, Conceptualization. H.C. and N.H.B.: Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. Wei Luo: Writing – review & editing, Conceptualization. N.R.: Writing – review & editing, Conceptualization. R.Y.: Writing – review & editing.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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Data Availability

Data will be made available on request.

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