Aedes albopictus Distribution in an Urban Area: Socio-ecological Evidence from a Socially Diverse Locality in Rawalpindi, Pakistan

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Abstract

Gulistan colony is a small and diverse urban patch in Rawalpindi. It is located alongside one of the biggest parks in the region, the Ayub Park. The park and its adjacent area, hosts many lakes, and hence supports lush green vegetation in the area. For this study ovitrap field sampling from the area was done which was used as input for the Maxent model for an analysis of high probability species distribution sites. Since, the area in focus is small, a high resolution bioclimatic variable dataset was constructed for the study area, using resampled satellite-based surface temperature and rainfall data. Qualitative analysis of the social determinants of vector growth and distribution was done, using a community survey. The study suggests that many of the green patches, particularly the ones alongside the main roads were the perfect breeding sites, for mosquitoes. This research also reported that land use landcover was the major determinant of carrier distribution, followed by bioclimatic variable Bio – 11 (temperature of the coldest quarter). It has also been observed that community practices of managing household water and waste can be a major contributing factor for the distribution of breeding of Aedes albopictus*.*

Keywords*:* Dengue, Ovitrap, Maxent, Socio-ecological Perspective, Vector-borne Disease.

Introduction

Since the last couple of decades, Pakistan has been directly affected by sporadic episodes of massive dengue outbreaks (Khan et al., 2016; Jahan et al., 2014; Mukhtar et al., 2011). It was initially reported in Karachi followed by a gradual growth of the spread of the vector to Lahore and subsequently to Rawalpindi (Homayoun et al., 2010). Generally, dengue outbreaks in Pakistan are reported between July and November,

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with the months from September to November, being the most severe (Fareed et al., 2016). It is believed that poor management of urban spaces coupled with a favourable temperature range between 20ºC and 30ºC and monsoon rainfall are the primary causes of high incidents of disease outbreak (Mutheneni et al., 2017). In a notable outbreak of dengue in Rawalpindi (Reza, 2016), the city reported a total of 3000 cases of infections, resulting in the loss of six lives, making it the worst hit city in the country that year (Reza, 2016). In 2019 however, it was reported that about 500 children with dengue fever were admitted at one hospital only (Asghar et al., 2019).

A combination of factors is responsible, for the prevalence and spread of dengue and its vectors. These are broadly classified as, ecological, biological, environmental, and socio-economic (Khalid et al., 2021). Considering that Pakistan has a diverse range of landforms, physical environmental conditions (Javed et al., 2022) and is densely populated in its plains (Shabbir et al., 2020), close to the equator (Lim et al., 2020). The prevalence of the disease presents a unique perspective. Growing conditions for the vector mosquito are favourable in most of these plains. These include, the presence of high population density, large household size (Shafique et al., 2022), proximity of built-up areas to water bodies (Kamal et al., 2022), presence of parks and recreational sites (Yuan et al., 2019), with high density of vegetative cover (Sekarrini, 2022), the prevalence of favourable temperatures for breeding coupled with high rainfall and poor maintenance of topography for good drainage (Lubna et al., 2023).

While these factors are known to be major contributors to the spread of dengue, no one factor has been found to be affective alone (Azim et al., 2023). In the context of Rawalpindi city, a vast variety of socio-economic conditions, physical conditions and dengue prevalence rates have been reported previously (Salam et al., 2023; Akhtar et al., 2022). In our study, several points were taken into consideration before approaching our research. These included the number of incidents reported every summer from the said locality, the presence of a major park in the vicinity of the study area (Yuan et al., 2021), the population of the study area, the high density of flora, and the diversity of income groups occupying the region. It was also of interest that one of the low-income sectors of the study area lies close to the Lai Nullah, a major river which post the flood season, leaves several ponds of stagnant water along its banks just next to the slums residing there (Shah et al., 2020). Hence, exposing a large population to the breeding sites of dengue vectors. Once a physically and socially dynamic location affected by the outbreak was selected, the next task was to see which factors are the dominant causes of the spread of the disease, in the given context.

Present study was divided into three parts as i) entomological survey to assess vector presence and density in the study area, ii) species distribution modelling to assess vector habitat, iii) social survey to qualitatively assess the practices influencing the distribution of vector species.

The reason for a comprehensive approach was the presence, of several required factors in one place. It would also lead to mapping the species distribution, the role of physical and bioclimatic variables in causing high prevalence, and how societal factors are contributing to them. Leading to good policy intervention and subsequent control. Since, most of the work done, in the region is devoid of these approaches, and previously has focused on the species distribution and climate only (Mustafa and Ahmed, 2022; Ahmed et al., 2020; Tariq and Zaidi, 2019).

Of the key idea behind using maximum entropy modelling for mapping species distribution was to be able to relate our field survey responses to social perception and understanding of species distribution in affected regions. Zaki et al. (2019) states that a vast majority of people are usually aware of dengue (~97%), its causes, and spread and would be willing (~67%) to help control its spread. However, there remains to be seen if this is universal as this study was conducted in Malaysia. Similar, studies by Wong and Abu Bakar (2013) in the past, and a more recent analysis from Indonesia by Kosasih (2021). However, the socio-economic situation in Pakistan is different and so is public perception and participation. Butt et al. (2020) found out that there is a general lack of seriousness towards health-related awareness. The issues are far ranging and damaging, since they are logistic, professional, lack of education and comprehensive national level programs. Shafique et al. (2022) found that intervention however, played a vital role in changing these perceptions, and was therefore successful in enforcing positive attitude among a focus group of 112 participants in Islamabad. Their focus was low-income communities and their perception to dengue. The field survey was then planned accordingly in areas where the species presence was found to be on a higher side, leading to a significant understanding of how the cause-and-effect relationship exits in the community. And if the same is missing, how is it transferring as a risk in the neighbourhood, despite greater awareness and means for preventive measures (Phuyal et al., 2022).

Proposed Methods

At 2300 acres, the Ayub National Park is one of the biggest parks in the Rawalpindi district of Pakistan. It is diverse as it is marked by a variety of land cover types, such as lakes, large green grassy patches, dense vegetation, an animal safari, and a cricket ground as well as an amusement park. Gulistan colony is a densely populated residential area bounded on one side by natural stream, the Lai Nullah, and on the other side by the park, separated by a highway (Figure 1). The residential settlement extends up to the edge of the stream. The residential area is also marked by a striking diversity of large properly managed houses, and small, landholding almost in a slum like condition by the river, with poor sanitation and drainage.

In the first phase of this research, field sampling survey has been conducted across the region in the breeding season of the mosquito. In the first stage it involved, field sampling (Figure 1) for dengue vectors using eggs collection. Six entomological field surveys each for two weeks were conducted in the months of July and August 2015. This data was required for modelling potential distribution sites for the vector and understanding the effect that land use land cover and associated climatic variables has on it. Egg collection was carried out from different natural (stone pools and tree holes) and artificial (pitchers, cisterns, drums, buckets, overhead water tanks, underground water tanks, air coolers) breeding habitats.

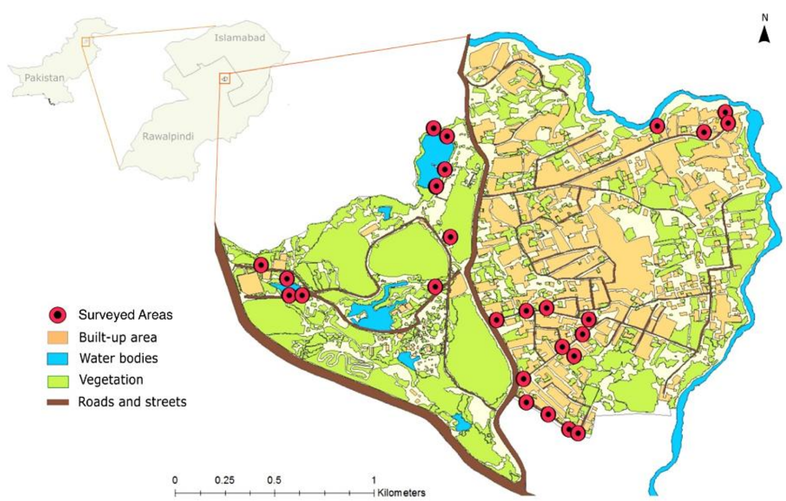

Figure 1: Map of the study area showing Ayub Park and Gulistan Colony in Rawalpindi where ovitrap sampling for dengue vector mosquitoes was carried out. The social survey was carried out in Gulistan Colony.

A total of 27 ovitraps were installed, out of which eleven were placed in the park and sixteen in the colony (Figure 2). Once the ovitraps were tested in the park, more were placed in the residential area. The ovitraps were placed randomly within sites that matched microhabitat suitability and accessibility. The sites were visited fortnightly to collect the ovistrips and service the traps. Ovistrips were collected in zipper bags and labelled. Ovitraps were cleaned, fitted with a new ovistrip, and filled with water.

The species were identified by using species identification keys provided in "Fauna of British India" by (Barraud, 1934). These larvae were then transported to the entomological lab and housed appropriated for quantification at the department of Zoology, University of Peshawar. The ovistrips that were collected were put under a microscope for examination. An egg count is an indirect measure of vector density. Calculated entomological parameters were including an Ovitrap index (Rozilwati et al. 2007), the average number of eggs (Rozilwati et al. 2007), and the ovitrap density Index (Manrique-Saide et al. 2014). The following formala was used for the peak period in August and September.

$$\text{Average number of eggs} = A/C$$
$$\text{Ovitrap Index} = B/C \times 100$$
$$\text{Ovitrap Density Index} = A/B \times 100$$

Where, A = Total number of eggs, B = Number of Ovitraps Positive (containing at least one egg), and C= Total number of Ovitraps

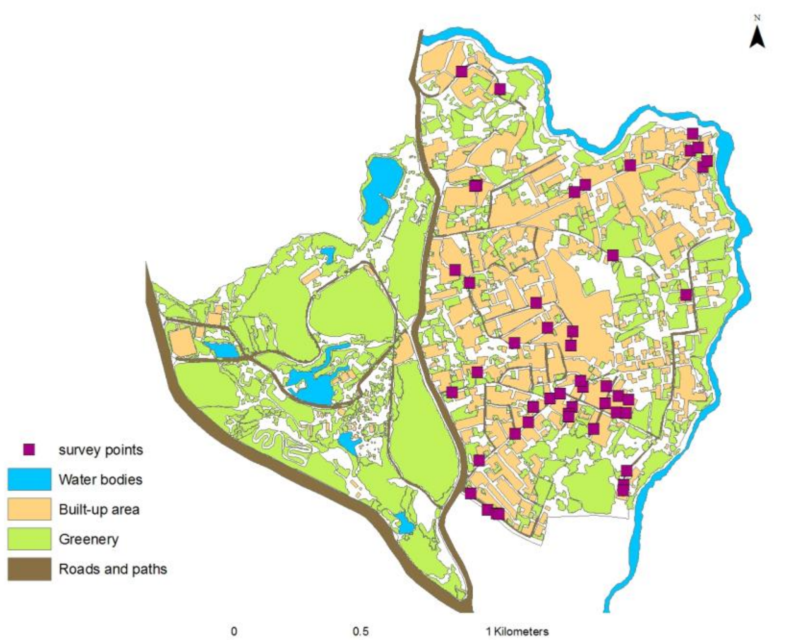

Figure *2: A qualitative social survey was conducted at household level, the locations of each household that was survey has been marked on the map.*

In the second phase of our research, a survey the households in the area to get an idea of the socio-economy of the area has been conducted. This perspective was necessary as it provides valuable insight that usually is left out by physical data-oriented studies. The survey was designed to be qualitative in nature, meaning that it was meant to identify individual practices, based on their socio-economic condition. The questions were groups in seven categories as, administrative, social, preventive approaches, personal awareness, medical history and economic.

Maxent (Phillips et al., 2006) was used to model probable species distribution patterns for the area. Maxent uses, species presence only data, and various variables, such as elevation, land use landcover, and bioclimatic variables, for species distribution model. The model is provided online as an easy to use, and quick to understand utility. It can use a variety of variables, based on the user preferences, for the study area. Maximum entropy models have been considered vital in species distribution modelling. Since they are effective, with only presence data, can efficiently overlook location data, and effectively work with a small dataset on presence locations (Baldwin, 2009). According to Philips et al. (2006) and Perera (2021) the model performs better at estimating probable occurrence sites, of the species as compared to other models.

Climate data is difficult to acquire in Pakistan at micro level. This is because of several reasons. One of the key factors, being lack of observatories in the country (Ullah et al., 2019). According to Ullah et al. (2021), there are a total of 53 meteorological stations in Pakistan. Which makes data availability at microlevel impossible and insufficient. In this regard and alternate approach was use, and climate variables, were generated using gridded weather data Moderate Resolution Imaging Spectroradiometer (MODIS) missions (Parselia 2019). The reason for temperature-based analysis was evident from the fact that dengue prevalence, is attributed to monsoon in South Asia, however the period of infections has been reported to vary, with some reporting it as early as the month of May and an intensification of the same towards September and November. Where rainfall has substantially reduced in the region (Treydte et al., 2006). It is the role of temperature, that appears to be far more evident in causing a wider spread of the disease. The primary role that rainfall plays however is of providing breeding grounds in the through ponds, and greenery (Prachyabreud, 2020).

Bioclimatic variables (Ramirez and Cabrera, 2009) were developed using temperature data from MODIS land surface temperature product (MOD11A1) obtained for the years 2000 onwards (Wan, 2006). It was processed to produce quality corrected LST maps, according to the methodology illustrated by (Neteler, 2010), resampled to 250 m, and then used to derive bioclimatic variables. Namely the bioclimatic variables, derived for the purpose of our work are mentioned in Table 1.

Since, the area was small and manageable, it was decided to map individual land feature types using manual digitization over the latest, google earth imagery. Built up area, vegetation, grasses, roads, pavements, greenbelts, and waterbodies were digitized. The data was used as an additional explanatory variable for species occurrence, distribution mapping (Alimi et al., 2015).

For presence data, entomological survey was conducted with field assistance from horticulturists in the area. The locations of species presence were marked using a field GPS unit. As normal with all field data, clusters are generated and hence, it was considered appropriate to spatially rarify the data (Bacaro, 2016). Climate heterogeneity was used as a factor for data rarefication. Graduated filtering approach was used, as it is considered appropriate for areas with different degrees of heterogeneity. 100 m was used as a distance variable for areas of low heterogeneity and 50 m in areas of high heterogeneity. After this 20 unique spatially independent sampling locations were scrutinized (Guler et.al., 2016).

Table 1: Bioclimatic variables derived using MODIS Land Surface Temperature datasets, MOD11A1, and was resampled using interpolation to 250 m. With the final selected variables as BIO5, BIO6 and BIO11, due to their uncorrelated nature.

S.No.	Code	Variable
1.	BIO1	Annual mean temperature
2.	BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
3.	BIO3	Isothermality (P2/P7) (* 100)
4.	BIO4	Temperature Seasonality (standard deviation *100)
5.	BIO5	Max Temperature of Warmest Month
6.	BIO6	Min Temperature of Coldest Month
7.	BIO7	Temperature Annual Range (P5-P6)
8.	BIO8	Mean Temperature of Wettest Quarter
9.	BIO9	Mean Temperature of Driest Quarter
10.	BIO10	Mean Temperature of Warmest Quarter
11.	BIO11	Mean Temperature of Coldest Quarter

Václavík et al. (2012) found that spatial autocorrelation, if removed can lead to improvements, in species distribution modelling. This also leads to better model performance, and efficiency in execution. Bioclimatic variables were minimized to the most uncorrelated one and retained the most ecologically important ones only. BIO5, BIO6 and BIO11 (Table 1) were observed to be uncorrelated at a threshold of Pearson's correlation coefficient of 0.7.

In the model parameters, it was set to replicate 10 times, with subsampling. While the test percentage was set at 20%. This led to the rest of presence location (80%) as calibration points, while the rest was used as test points for model evaluation. A default prevalence was chosen to be at 0.7.

Results

Our entomological survey showed that only *Aedes albopictus* was found in the study area. No *Aedes aegypti* was reported from any of the larvae positive containers, despite the survey period being the peak mosquito breeding season. A total of 4,341 sites were surveyed for the presence of larvae, of which 253 were observed positive for the presence of larvae giving a mean HI of 5.8% (Table 1). Number of containers (natural and artificial) surveyed for larvae were 4987 and 377 of them were harbouring larvae giving a CI value of 7.56%. Total number of larvae collected varied between 458 larvae from 33 containers to 3,649 larvae from 107 containers (Table 2). Maximum value of HI and CI were observed for visit 5 while minimum for visit 3.

Table 2: Number of eggs collected from ovitrap sampling for each biweekly visit during July-September 2015. The shaded area shows the additional Indices of Vector Density.

	Visit 2 (14.07.2015)	Visit 3 (29.07.2015)	Visit 4 (13.08.2015)	Visit 5 (27.08.2015)	Visit 6 (15.09.2015)
Total number of eggs	458	819	3214	3649	2356
Number of ovitraps positive	6	6	22	23	20
Total number of ovitraps examined	7	6	22	24	21
Ovitrap Index	85.7%	100%	100%	95.83%	95.24%
Mean number of eggs	76.33	136.5	146.09	152.04	112.19
Ovitrap Density Index (ODI)	76.33	136.5	146.09	158.65	117.8

Species distribution modelling is impacted by the scale of the study. The modelling results reflect the vector habitat suitability in a small urban patch with heterogeneous features. Model results show that the distribution probability of *Aedes albopictus* is highest in trees and bushes in the park and the colony (Figure 3a). One of the strongest influencing factors for species distribution in the model was found to be the land cover variables, at 75% (Figure 3b). Of these the trees were the higher impact features followed by roads. This can be attributed to the presence of green belts and dense vegetation along the pavements. While built up areas and waterbodies, seems to have the least influencing factors. However, in retrospect waterbodies have the most influence on greenery and similar, built-up areas are places, where these species look for potential hosts. BIO

11 was the most significant environmental contributor followed by BIO5, with their respective influences being at 4.2 and 2.2%, respectively.

Based on regularized training gains, the jackknife test for variable importance also indicated land cover as the variable containing by far the most valuable information for modelling potential habitat sites (Figure 4). The calculated AUC for the training/calibration points was 0.780, slightly higher than the test data AUC which came out to be 0.735.

For the social, environmental, economic, and administrative factors affecting vector presence in Gulistan colony, the community survey provided vital insights. The community is spread in a manner that is common to most Pakistani societies. The main planned area remains inhabited by the affording social class, while the lower or dependent social classes, start off with slums and huts in the farthest least provided parts, away from the planned or claimed land for formal administrative allocation. The houses that were a part of the planned allocation are situated towards the park on the southwestern part. While there are houses located on the northeastern fringes towards the Lai Nullah (an urban stream) that is densely populated and mostly inhabited by a socioeconomic stratum that is not comparatively well provided. Their houses being in direct exposure to the floods from the Nullah, and nearby dry parts, providing good breeding grounds to the mosquitoes.

Of the survey community it was observed that a large percentage of the households were educated (~66%) and had college level degrees. About ~6% of the houses reported a previous infection of dengue and 6% reported that they had at least one member, affected recently. One thing that was remarkable was the community mixing that happens in the locality. This is partly due to their collective proximity to the Ayub Park and to the fact that most of the low-income community members, work as household help in the affording segments. Leading to an equal amount of exposure to dengue.

Water supply and sanitation play a vital role in spread of vector borne diseases (Lowe et al. 2021). In the absence of regular water supply which here is ~59% of the community the people are bound to store water in containers, which in many cases turn out to be uncovered, and provide good breeding grounds for the species. Houses that were poor, out of the planned limitation of the colony are naturally not covered by the municipal supply network. They resort to either groundwater for their basic requirement or alternatively access the nearby community facilities for collecting water. It was noted that, ~24% of the households stored water in containers for drinking and washing purposes, and notably ~81% covered them. Also, ~14% of the surveyed houses kept vessels such as plant dishes, coolers etc. This is a common behaviour also reported by

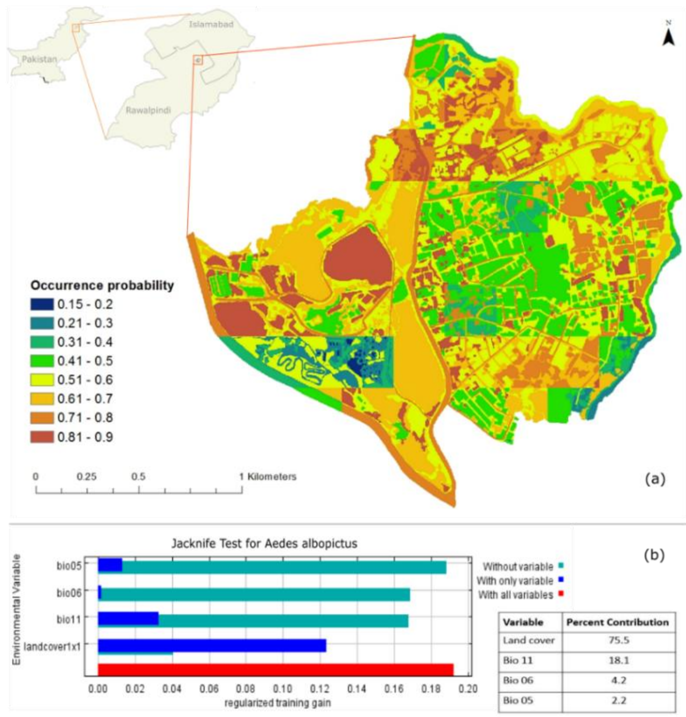

Figure 3. (a) The probability map showing the distribution of* Aedes albopictus *in the study area, (b) along with the jack-knife test of variable contribution.

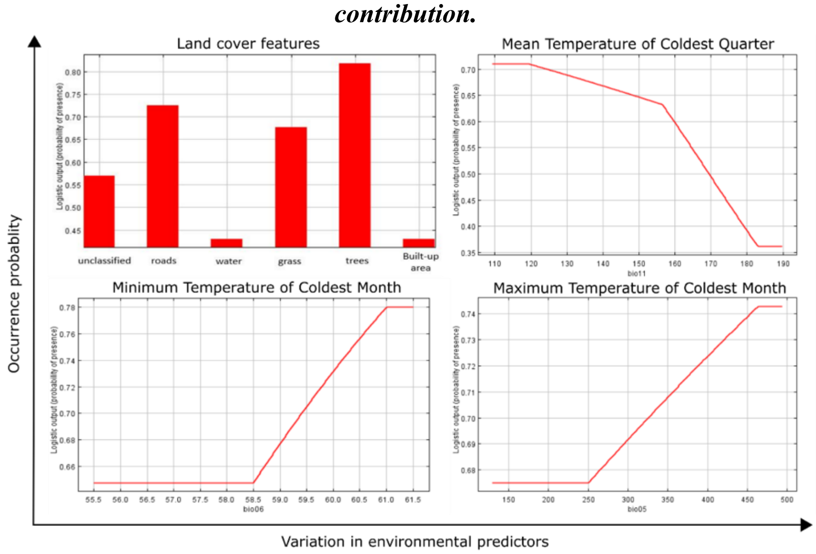

Figure 4. Response curves of the predictor variables show how each variable impacts the model output.

many others in Pakistan (Awan et al., 2022; Zainab et al. 2021).

Additional there is a serious concern in the community regarding waste disposal facilities. It is a common practice in Pakistan to dispose of waster improperly since, a majority does not have access to a managed facility (Akmal and Jamil, 2021). It was found that ~22% of the households had access to managed waste disposal facilities and smaller housed by the stream, resorted to dumping their waste on its banks, hoping for it to be washed away by water or floods (Imtiaz et al., 2021). One important observation was that ~66% of the community households covered their water baskets. This is unique in a situation where a vast majority in the end will have to dispose their waste in open. Leading to a very common distribution of heaps of garbage in the vicinity of houses.

Government campaigns in the region on dengue awareness usually are in full swing by the month of May and ends towards November (Ahmed et al., 2023). Amar et al. (2023), however, believes that the disease remains neglected in Pakistan and needs a furthering of efforts to generate knowledge. On the contrary it has been observed that ~94% of the people were able to mention traits of an *Aedes* mosquito and were of the view that they can easily identify the dengue vector. In case of the breeding habitats, while knowledge remained lower still a good ~80% were aware of the habitats the mosquito prefers as its breeding grounds. Campaign posters were commonly seen in the locality and the community was aware of the running media campaigns in this regard. They had sufficient knowledge of the preventive measure they need to take at personal level to avoid a mosquito bite and subsequent infection.

As many as ~44% of the households informed us that awareness teams have reached them and informed them on the measures to take to avoid dengue outbreaks. Respondents suggested that while fogging in insecticide sprays were common, their reach was not effective, particularly in the farthest parts of the community that is towards the river.

Discussion

One of the key observations, in the context of species distribution, is that *Aedes albopictus* has become a dominant species in the region (Nejati et al., 2020). Bonizonni et al. (2013) however, points towards another concern in this regard that is its higher disease transmission capacity. This is contested for Zika virus, by Lozano-Fuentes (2019), but Bara et al. (2015) and Paupy et al. (2009) argue that its higher invasive nature and larval tendency to resist serious changes in environmental conditions, has allowed for its greater spread, dominance, and vectorial capacity thereof.

Nasir et al. (2016), based on one of their surveys of *Aedes aegypti* population in the city reported that in a variety of surveyed sites in 2010 and 2011, they were able to find *Aedes aegypti*. On the contrary, Mukhtar et al. (2011) found *Aedes albopictus* to be dominant in Rawalpindi as compared to the rest of Punjab. In this given situation the arguments by Vega-Rúa et al. (2020) on its greater survivability and invasiveness are important. And particularly on the temperature resistance of *Aedes albopictus* by Cunze et al. (2016).

One of the key considerations in species distribution modelling remains the availability of high-resolution data. While our land use and landcover data, which has by far dominated the distribution output was the best possible, other datasets, tend to lack in term of resolution (Guillera-Arroita et al., 2015). This is a common issue with many studies that are multidisciplinary in nature and used spatial data (Karge et al., 2017). The presence of high-resolution data is rare and usually difficult or expensive to collect.

Vegetation as many other studies Martin et al. (2023); Camargo et al. (2021); Sanders et al. 2020; Little et al. (2017) have suggested is the key distribution defining element of the *Aedes albopictus* distribution. In our analysis it has been observed that taller trees and plants to be more conducive as their habitat as compared to grasses. This seems ecologically consistent as these offer the necessary shades and are usually less disturbed by human movement. Hence convenient for ovipositioning by the mosquitoes. Roads and pavements were two other elements modelled as critical for the mosquitoes, distribution. However, this can either because of the dense vegetation along the roads, the presence, of potholes or factors such as the temperature they create. The road is lines immediately next to a wide patch of bushes and separated by a wastewater drainage channel.

The role of water bodies here, is complex. While they are massive in the region in the form of lakes and the nearby nullah, they do not offer stable and protected grounds for the mosquitoes to breed. In fact, one of the observations was that the lakes are home to fishes and are also used for recreational water sports. But they have a significant contributing role, as they are close to bushy vegetation and are supportive of their growth.

Like previous studies on the subject (Tsuda et al., 2015; Lohmus and Balbus, 2015; Medeiros-Sousa et al., 2015), our work therefore reinforces that pavements and plants, lead to a greater concentration of the *Aedes* mosquitoes, and subsequent threat of infections. One of the factors, that have been failed to consider so far is to identify, the dominant species of plan types and their association with the larvae prevalence.

One of the explanations for the dominant role of land cover as the predictor variable is the nature of present classifications, within the variable itself. The fact that classes are clearly defined, and bears, a greater spatial detail has led to its defining role (Westby et al., 2021). In cases where survey of temperature variables at a finer scale can be done, present study consider that the effect of bioclimatic factors will improve. At the given spatial resolution of bioclimatic data, it seems nearly impossible to have sharp variations, mapped and bear subsequent impact on the modelling process. Nevertheless, such data can be considered useful for regional continental scale modelling. (Mehrabi et al., 2014) suggested that insects tend to respond to finer scale variations in the environment. Which most bioclimatic data already available or generated through spatial satellite remote sensing records lack (Kriticos et al., 2012; Soria-Auza et al., 2010).

The AUC for training data of 0.780 showed good predictive performance (Gwitira et al., 2015; Baldwin, 2009) of the model on calibration. It offers a widely accepted and valuable criteria for model performance evaluation (Gwitira et al. 2015; Kramer-Schadt 2013). Our training data AUC of 0.780 showed good predictive performance and a test data value of 0.735 shows that the model was able to generalize prediction to the test points.

One of the key contributors to the spread of dengue, in developing world are the water storage practices (Mahmud et al., 2022). These are the main breeding sites, for the *Aedes* mosquito and proper, management of water ensures, that infections are controlled effectively (Tsuzuki et al., 2009). However, it has been observed that since water supply is sketchy and not regular in a greater part of the community, it leads to improper storage, in buckets and containers, that are not covered. Leading to the availability of a conducive, breeding environment for the mosquitoes (Khan et al., 2022).

Improper waste disposal is believed to be another cause of the spread of *Aedes* mosquitoes and result in increased dengue transmission (Bohra and Andrianasolo 2011). In the surveyed community it has been observed that, many of the residents, resorted to improper waster deposal and subsequent, provisioning of breeding grounds for the species. For instance, wrappers, card boxes, bottles etc. in waste can collect water from rain, and serve as breeding sites for the vectors. Also, mosquitoes, hide in uncovered waste bins and can find a potential host in the next person, approaching the waste bins, for dumping. Good waste collection practices have been found to reduce the risk of mosquito prevalence (Abeyewickreme, 2012). Sobral and Sobral (2019) found that an increase of 1000 tones in proper garbage collection led to a 0.032 decrease in dengue cases. This is crucial for the said area, since most of the water is disposed in open area, and the disposal near the river remains highly inaccessible to garbage collection trucks.

There is a negative correlation between dengue and literacy (Guha-Siper and Schimmer, 2005). Since, a higher literacy means a generally better awareness and efficiency of the public awareness campaigns, too. As Meleo-Erwin et al. (2020) based on the readability and understanding analysis of dengue related material online found out that a vast majority of the published material on the subject, for general awareness remains little understandable. It is also important to consider that a higher literacy is also related to higher incomes and better affordability of preventive means.

Since our work was done, after a recent report of diseases outbreak in the area in the preceding year. It was found that people at large were aware of risks with the spread of dengue, and the preventive measures, that they can take. But in the wake of municipal services, not being thoroughly effective in the area, and affordability low in some parts, of the community. The necessary preventive measures did not appear fully in place. In addition to this the natural mixing due to the community and its proximity to a highly frequented park form the entire twin city region of Rawalpindi and Islamabad can be explanatory variables for an increased risk of infection due to *Aedes* prevalence. It has also been proposed to investigate the same for all parks, in the twin cities for future studies.

Conclusion

It has been found that *Aedes albopictus*, is the dominant prevalent species of dengue in the region. This owes partly to the divers and rather challenging temperature regime of the region. It has also been found that, land cover plays a far more significant role in model prediction, as compared to spatial environmental data. It is in part due to the higher spatial resolution of landcover data and comparatively poor resolution of environmental variable datasets. However, with the advent of spatial data collection sing Internet of Things (IoT), it has been observed that studies can strive to use these tools in future environmental variables mapping. Nevertheless, the task remains daunting and complex at large. Thick vegetation was crucial to higher growth rates of the mosquito and most of the samples, were found near and around them. Similarly, the model was able to identify the same as perfect habitat for the species. Waterbodies on the contrary due to their mixed nature were not found to be the perfect sites for abundance of the *Aedes albopictus* species. During the study it has been revealed that the park authorities particularly were aware of the need to ensure that the population of the mosquitoes is effectively controlled near these waterbodies as they are the primary spots of interest for the visitors. However, towards the Nai Nullah, it was the natural flow of the water, that hindered the greater spread of the mosquito species. The higher impact of the temperature of the coldest quarter (BIO11) on species distribution was correspondent to the observations that dengue infections peak during the September to November period (Akram et al., 2022).

The community awareness following dengue outbreaks has translated into residents adapting their lifestyles to deal with the threat of disease. Lack of proper water supply and waste disposal facility contribute to spread of vector in the study area. Species dispersal is also aided by the water and waste management practices of the community. Insecticide spraying on vegetation, proper water supply, and proper waste management may help in controlling dengue vector and preventing an impending outbreak in future.

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References

Abeyewickreme, W., Wickremasinghe, A. R., Karunatilake, K., Sommerfeld, J., & Axel, K. (2012). Community mobilization and household level waste management for dengue vector control in Gampaha district of Sri Lanka: An intervention study. *Pathogens and Global Health, 106*(8), 479–487.

Akhtar, N., Kawish, A. B., Tahir, Q., Butt, A. M., & Hameed, S. (2022). Awareness regarding dengue prevention and control in peri-urban union councils of Tehsil Rawalpindi. *Pakistan Biomedical Journal*, 290–295.

Akmal, T., & Jamil, F. (2021). Assessing health damages from improper disposal of solid waste in metropolitan Islamabad–Rawalpindi, Pakistan. *Sustainability, 13*, 2717.

Akram, M. I., Akram, W., Qayyoum, M. A., Rana, A. A., Yasin, M., & Saddiq, B. (2022). Vector indices and meteorological factors associated with dengue. *Environment, Development and Sustainability*, 1–12.

Alimi, T. O., Fuller, D. O., Qualls, W. A., Herrera, S. V., Arevalo-Herrera, M., Quinones, M. L., & Beier, J. C. (2015). Predicting potential ranges of primary malaria vectors and malaria in northern South America based on projected changes in climate, land cover, and human population. *Parasites & Vectors, 8*, 1–16.

Asghar, R. M., Ashraf, R. R., Saheel, K., & Hussain, A. (2021). Evaluation of haematological changes in paediatric dengue fever patients during the 2019 outbreak. *Journal of Rawalpindi Medical College, 25*.

Awan, N. J., Chaudhry, A., Hussain, Z., Baig, Z. I., Baig, M. A., Asghar, R. J., Khader, Y., & Ikram, A. (2022). Risk factors of dengue fever in urban areas of Rawalpindi district in Pakistan during 2017: A case–control study. *JMIR Public Health and Surveillance, 8*(1), e27270.

Azim, S., Nawab, S., & Ali, N. (2023). Relative abundance, distribution, and diversity of mosquitoes in District Peshawar, Charsadda, and Swabi. *Asian Journal of Research in Zoology, 6*(1), 7–19.

Bacaro, G., Altobelli, A., Cameletti, M., Ciccarelli, D., Martellos, S., Palmer, M. W., & Chiarucci, A. (2016). Incorporating spatial autocorrelation in rarefaction methods. *Ecological Indicators, 69*, 233–238.

Baldwin, R. A. (2009). Use of maximum entropy modeling in wildlife research. *Entropy, 11*(4), 854–866.

Barraud, P. J. (1934). *The fauna of British India, including Ceylon and Burma: Diptera (Vol. 5, Culicidae)*. Entomological Society of London.

Bohra, H., & Andrianasolo, H. (2011). Application of GIS in modeling of dengue risk based on sociocultural data: Case of Jalore, Rajasthan, India. *Dengue Bulletin, 25*, 92–102.

Camargo, C., Alfonso-Parra, C., Díaz, S., Rincón, D. F., Ramírez-Sánchez, L. F., Agudelo, J., & Avila, F. W. (2021). Spatial and temporal population dynamics of male and female *Aedes albopictus* at a local scale in Medellín, Colombia. *Parasites & Vectors, 14*(1), 312.

Cunze, S., Koch, L. K., Kochmann, J., & Klimpel, S. (2016). *Aedes albopictus* and *Aedes japonicus*: Two invasive mosquito species with different temperature niches in Europe. *Parasites & Vectors, 9*, 1–12.

Guha-Sapir, D., & Schimmer, B. (2005). Dengue fever: New paradigms for a changing epidemiology. *Emerging Themes in Epidemiology, 2*(1), 1.

Guillén-Arroita, G., Lahoz-Monfort, J. J., Elith, J., Gordon, A., Kujala, H., Lentini, P. E., & Wintle, B. A. (2015). Is my species distribution model fit for purpose? *Global Ecology and Biogeography, 24*(3), 276–292.

Kriticos, D. J., Webber, B. L., Leriche, A., Ota, N., Macadam, I., Bathols, J., & Scott, J. K. (2012). CliMond: Global high-resolution historical and future scenario climate surfaces for bioclimatic modeling. *Methods in Ecology and Evolution, 3*(1), 53–64.

Lim, J. T., Dickens, B. S., Haoyang, S., Ching, N. L., & Cook, A. R. (2020). Inference on dengue epidemics with Bayesian regime switching models. *PLoS Computational Biology, 16*(5), e1007839.

Little, E., Biehler, D., Leisnham, P. T., Jordan, R., Wilson, S., & LaDeau, S. L. (2017). Socio-ecological mechanisms supporting high densities of *Aedes albopictus* in Baltimore, Maryland. *Journal of Medical Entomology, 54*(5), 1183–1192.

Lowe, R., Lee, S. A., O'Reilly, K. M., Brady, O. J., Bastos, L., Carrasco-Escobar, G., & Gasparrini, A. (2021). Combined effects of hydrometeorological hazards and urbanization on dengue risk in Brazil. *The Lancet Planetary Health, 5*(4), e209–e219.

Mahmud, M. A. F., Abdul Mutalip, M. H., Lodz, N. A., Muhammad, E. N., Yoep, N., Hasim, M. H., Rahim, F. A. A., Aik, J., Rajarethinam, J., & Muhamad, N. A. (2022). Environmental management methods in combating dengue: A systematic review. *International Journal of Environmental Health Research*, 1–20.

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling, 190*(3–4), 231–259.

Lubna, Rasheed, S. B., & Zaidi, F. (2023). Species diversity patterns of mosquitoes breeding in container habitats of Peshawar, Pakistan. *Brazilian Journal of Biology, 84*, e271524.

Salam, M. A., Shah, S. A., Zafar, F., Naseer, M., Irshad, I., Shoukat, S., & Abedien, Z. U. (2023). Dengue fever epidemiological investigation in Rawalpindi. *Journal of Pharmacy & Negative Results*, 2648–2655.

Sanders, J. D., Talley, J. L., Frazier, A. E., & Noden, B. H. (2020). Landscape and anthropogenic factors associated with adult *Aedes aegypti* and *Aedes albopictus*. *Insects, 11*(10), 699.

Sekarrini, C. E. (2020). Mapping of dengue hemorrhagic fever vulnerability based on geographic information systems in Lubuk Linggau City. *Sumatra Journal of Disaster, Geography and Geography Education, 4*(1), 63–67.

Shabbir, W., Pilz, J., & Naeem, A. (2020). A spatial–temporal study of dengue spread depending on climate factors in Pakistan. *BMC Public Health, 20*, 1–10.

Shafique, M., Mukhtar, M., Areesantichai, C., & Perngparn, U. (2022). Effectiveness of positive deviance to improve dengue knowledge. *Insects, 13*(1), 71.

Sobral, M. F. F., & Sobral, A. I. G. D. P. (2019). Dengue cases and urban waste collection. *Ciência & Saúde Coletiva, 24*, 1075–1082.

Tariq, B., & Zaidi, A. Z. (2019). Geostatistical modeling of dengue disease in Lahore, Pakistan. *SN Applied Sciences, 1*, 1–12.

Treydte, K. S., Schleser, G. H., Helle, G., Frank, D. C., Winiger, M., Haug, G. H., & Esper, J. (2006). The twentieth century was the wettest period in northern Pakistan. *Nature, 440*(7088), 1179–1182.

Tsuda, Y., Maekawa, Y., Ogawa, K., Itokawa, K., Komagata, O., Sasaki, T., Sawabe, K., & Isawa, H. (2016). Biting density of *Aedes albopictus* during the 2014 dengue outbreak in Tokyo. *Japanese Journal of Infectious Diseases, 69*(1), 1–5.

Ullah, W., Wang, G., Ali, G., Hagan, D. F. T., Bhatti, A. S., & Lou, D. (2019). Comparing precipitation products over Pakistan. *Remote Sensing, 11*(6), 628.

Václavík, T., Kupfer, J. A., & Meentemeyer, R. K. (2012). Accounting for multi-scale spatial autocorrelation improves invasive species distribution models. *Journal of Biogeography, 39*(1), 42–55.

Wan, Z. (2006). *MODIS land surface temperature products users' guide*. University of California, Santa Barbara.

Westby, K. M., Adalsteinsson, S. A., Biro, E. G., Beckermann, A. J., & Medley, K. A. (2021). *Aedes albopictus* populations and larval habitat characteristics across urban and rural landscapes. *Insects, 12*(3), 196.

Wong, L. P., & AbuBakar, S. (2013). Health beliefs and practices related to dengue fever. *PLoS Neglected Tropical Diseases, 7*(7), e2310.

Yuan, B., Lee, H., & Nishiura, H. (2019). Assessing dengue control in Tokyo, 2014. *PLoS Neglected Tropical Diseases, 13*(6), e0007468.

Yuan, B., Lee, H., & Nishiura, H. (2021). Analysis of international traveler mobility patterns in Tokyo to identify geographic foci of dengue fever risk. *Theoretical Biology and Medical Modelling, 18*(1), 1–10.

Zainab, N., Tariq, A., & Siddiqui, S. (2021). Development of a web-based GIS alert system for dengue risk in Pakistan. *Geosfera Indonesia, 6*(1), 77–95.

Zaki, R., Roffeei, S. N., Hii, Y. L., Yahya, A., Appannan, M. A., Said, M. A., Hairi, N. N., Bulgiba, A., Quam, M., & Rocklöv, J. (2019). Public perception and attitude towards dengue prevention and early warning in Malaysia. *PLoS ONE, 14*(2), e0212497.