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Investigating the impact of changing environments on mosquito-borne diseases, through the lens of alterations in vegetation and human-driven landscape modifications

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Abstract

From a public health perspective, they pose myriads of challenges as the environment and its factors can enhance or inhibit their spread. This paper attempts to analyze the influence of changing vegetation cover and anthropogenic land use on the patterns and rates of mosquito-borne disease incidence. Changes in natural systems due to urban encroachment, deforestation, and farming create new habitats, modify microclimates, and change the population structure of mosquitoes. This study combines remote sensors, ecological simulations, and epidemiological techniques to test the correlation between certain diseases and changes in land cover. We study how different sets of vegetation affect the activities of mosquitoes, their mid-summer reproductive rate, and the interactions between parasites and vectors. The research explores the impacts of human land use activities like urbanization and deforestation on ecosystems and the frequency of human contact with natural organisms. This research provides links to understanding the consequences of changing the environment in the context of historical and geospatial records of diseases such as malaria, dengue, and Zika. Understanding the relationship between environmental shifts and the distribution of vector-borne infections suggests the need for holistic disease management strategies.

Keywords: Urbanization; Deforestation; Migratory global warming; Mosquito-borne infections

1. Introduction

Land use patterns such as urbanization, deforestation, migratory global warming, and other aspects of environmental change have proven to be a factor of keen interest in the impact they have on the frequency of mosquito-borne infections. This consideration of these diseases is because their geographical domains are continuously expanding. The unique ecology of each region, in combination with new socio-demographic and lifestyle changes, poses an unprecedented challenge. Vectors like Ae. Aegypti, An. Gambiae and Culex species have population structures and disease transmission potential that are affected by changes in land cover, human activity, and vegetation alterations, which depend on ecological changes. With humans further developing the natural landscape, the conditions that foster vector breeding, as well as the survival and host-seeking activities, change, and in concomitance, so does the incidence and spatial distribution of the diseases. The shift towards ‘build and invest’ industrial models have been facilitated and aggravated by the steady growth and readiness of globalization and climatic change [1]. These things are also the product of drastic changes the environment has faced, such as increased telecommunications, ease of travel, lifestyle choices, and so much more. This all of course leads to a problem that is larger than what has been provided. Vectors like Ae. Aegypti, An. Gambiae and Culex species have population structures and disease transmission potential that are affected by changes in land cover, human activity, and vegetation alterations, which focus on ecological changes. With humans further developing the natural landscape, the conditions that foster vector breeding on the survival and host-seeking activities change, and in concomitance, so do the incidence and spatial distribution of the diseases. Alongside

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rampant land use changes came greater availability of water, land space, and a microclimate in the rampant sustenance of malaria, dengue, chikungunya, and the Zika virus. With the diseases burdening the population already set at risk, it is important to assess how environmental alterations such as urban development and plantation growth.

There is considerable literature on the environmental factors of mosquito-borne diseases, but a deeper understanding of how particular changes in vegetation and anthropogenic landscape alterations affect vector-host relationships and disease spread is lacking. Remote sensing and Geographic Information Systems (GIS) are rapidly becoming important tools for monitoring land use changes and estimating vector distribution movement. Furthermore, ecological modeling techniques along with epidemiological data allow for more thorough insight into how changes in vegetation cover structure, as well as land use changes, affect the risks of diseases. Through the combination of multiple datasets, researchers can create models to predict disease outbreaks and focus intervention measures accordingly [2]. The research aims to examine the way vegetation shifts as well as anthropogenic landscape alterations systematically affect the spread of mosquito-borne diseases. This study has adopted a multidisciplinary design that includes ecological modeling, remote sensing, and epidemiological studies to determine how environmental changes impact the dynamics of vector and disease relationships. Reconciling these connections is important for formulating efficient strategies to control disease vectors and informing pertinent health policies to reduce the consequences of mosquito-borne diseases in a continuously changing environment. The results of the research are anticipated to give useful information on eco-friendly land use methods and urban development policies that reduce opportunities for disease spread and protect the environment at the same time. Figure 1 illustrates the concept of changing environments on mosquito-borne diseases:

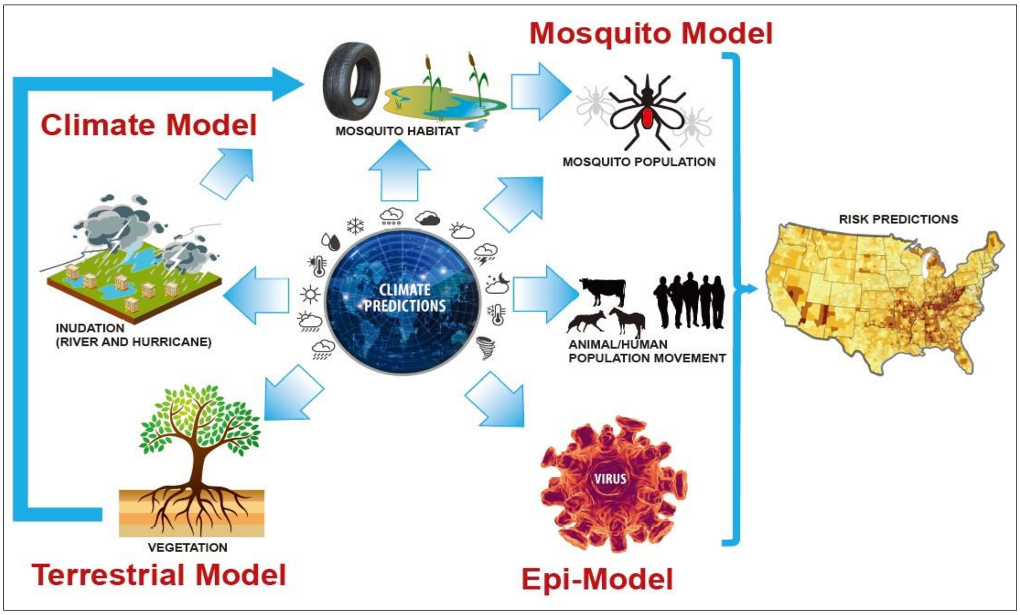


Figure 1 Concept of changing environments on mosquito-borne diseases

Changes in the landscape made by humans, such as increasing urban areas, cutting down forests, and building irrigation systems and dams, have created novel epidemiological risks by changing the distribution of potential breeding sites and the interaction between hosts and vectors. Urbanization has been one of the major drivers of the distribution of Aedes mosquitoes, which are common in densely populated regions due to the presence of artificial water storage containers, plastic waste, and drained septic tanks. These anthropophilic mosquitoes have developed rapid urban expansion of informal settlements without proper water supply and sanitation, further aggravating the situation, and causing outbreaks. Although there are established correlations between a changing environment and the spread of mosquito-borne diseases, there is still a lack of sufficient and detailed information as to how certain changes in the terrain impact mosquito populations in the ecosystem. The use of remote sensing in combination with spatial epidemiology is capable of addressing this challenge by enabling the identification of high-risk areas as well as effectively improving the precision of predictive models for the disease. Using advanced machine learning algorithms on satellite images can enable real-time detection of shifts in terrain, which can stimulate the deployment of intervention plans to mitigate potential risks. In addition, having access to straightforward and reliable entomological information would also enable these models to be more comprehensive and facilitate rational decisions concerning vector management programs. In that sense, this research aims to be another building block toward a comprehensive understanding of the roles that changes in vegetation and anthropogenically altered landscapes have on the transmission cycles of mosquito-borne diseases [3]. This study seeks to offer practical solutions for the environmental issues behind vector-borne diseases by integrating ecological data, epidemiological investigations, and geospatial information. The outcomes will contribute to the understanding of public health and will enable the implementation of urban and land construction development policies with ecological sustainability in mind. During an era of drastic environmental shifts, taking preventative measures towards vector surveillance and control is necessary to reduce the likelihood of future disease outbreaks and strengthen global health security.

2. Literature Review

Numerous ecological studies and epidemiological research have decided to explore the relationship that exists between changes in the environment and diseases that are transmitted by mosquitoes. Researchers have pointed out that changes in vegetation, urban areas, and land modifications have a profound impact on the transmission patterns of certain diseases like malaria, dengue fever, Zika, and chikungunya. Several studies have shown that changes in natural habitats directly affect the abundance, distribution, and host-seeking behavior of the vectors (Reiter, 2001; Patz et al., 2004). For example, Reiter (2001) cited evidence that Aedes aegypti mosquitoes have increased in numbers because urban areas now provide good breeding sites in the form of standing water in artificial containers which are very common in highly populated urban areas with poor water supply systems. The rapid growth of cities in Sub-Saharan Africa has increased malaria transmission by increasing the number of stagnant water containers that Anopheles mosquitoes prefer. These findings go in line with Wilke et al. (2019) whose work showed that the alteration of vegetation and urban infrastructure increased the local density of some disease vectors resulting in more frequent vector-human contact and more disease cases. In regions around the globe, deforestation has had a substantial impact on altering the patterns of mosquito growth. This is especially witnessed in tropical and subtropical areas where land is cleared on a large scale. As a result, the predators and prey that were present naturally break down and the microclimatic conditions change. According to research conducted by Vittor et al. In 2006, deforestation of Peru's Amazon rainforest resulted in a surge of *Anopheles Darlingi* which is the main malaria carrier in the region. This was largely caused by the formation of sunlit pools where larvae could thrive in abundance. Such findings were also supported by Laporta et al. In 2013 where the deforestation of the Brazilian Atlantic Forest changed the dynamics of malaria transmission, with higher rates of transmission in areas that were converted to agricultural settings. On the opposing side, research conducted by Chaves et al. in 2008 showed that there are instances where the cutting down of trees can lessen the rates of diseases caused by mosquitos such as malaria by destroying the essential places where they breed. Even though such reductions are common, they are at the same time, temporary [4]. New forms of land use such as irrigation or agricultural expansion increase the amounts of places where the carrier populations can thrive such as breed sites.

Mosquitoes have also been studied in the context of urbanization and its impact on disease transmission. *Culex pipiens* (common mosquito) is well spread in the world due to its tolerance towards urban cities. Gubler (2011) says that this species is especially abundant in urbanized tropical developing countries. The study emphasized that uncontrolled urbanization results in the storage of stagnant water in containers, tires, and construction sites, which are all suitable for breeding. Ebi and Nealon (2016) showed that the urban heat island effect causes people living in highly populated areas to be at greater risk of disease because the elevated temperatures facilitate the survival of mosquitos and the replication of viruses. However, Lambin and others (2010) point out that some modern urban areas adopt good vector control policies and efforts, which benefit people by providing proper waste disposal and drainage services, which, in return, reduce breeding sites for mosquitos and consequently lower the prevalence of mosquito-borne illnesses. Thus, the matter of urbanization and disease relation is the core of mystery that needs the touch of context, environmental factors, and social and economic conditions of a certain area.

The role vegetation plays in the ecology of mosquitos has drawn attention from researchers. As Afrane et al. (2012) have shown in Figure 2, mosquito survival is more frequent in areas with plants because there is vegetation, which maintains relative humidity, and water bodies that serve as sites for larvae development. On the other hand, Foley et al. (2005) reported that oil palm and rubber monoculture plantations' modification of ecosystems may enhance or reduce the abundance of mosquitoes based on how such waters are managed. A different perspective was noted by Laporta and Sallum (2021) who have pointed out the necessity of maintaining ecological balance by suggesting that significantly diverse ecosystems can serve as a natural control for the population of mosquitoes. Remote sensing and spatial analysis have proved useful in assessing the effects of environmental changes on the spread of epidemics caused by mosquitoes. For instance, Hay et al. (2005) show that satellite images coupled with Geographic Information System (GIS) provide a simple way to track changes in vegetation and map regions that are likely to support the breeding of disease vectors.

Figure 2 The role vegetation plays in the ecology of mosquitos

In the same way, Rochlin et al. (2013) assessed the impact of urban development on the distribution of Aedes albopictus in the northeastern United States through remote sensing and were able to conclude that landscape fragmentation was vital in vector distribution. More recently, Mordecai et al. (2019) have started using climate models together with remote sensing to predict geographic range shifts of mosquito species in the face of environmental changes such as global warming and land-use changes. Taken together, these findings stress the need for combining ecological, epidemiological, and geospatial science to effectively address the problem of diseases caused by mosquitoes. The existing literature strongly suggests that environmental phenomena in particular changes in vegetation as well as anthropogenic modification of the landscape are the most important drivers of mosquito-borne disease dynamics. Although urbanization, deforestation, and climatic change have significant attention, there are still gaps in construing predictive models that can incorporate the interactions of these factors. Integrating remote sensing, ecological modeling, and epidemiological surveillance opens new horizons for improving targeted vector control methods [5]. Due to the continuous risk posed by mosquito-borne diseases at the global level, it is critical to develop and implement mitigation policies on multi-disciplinary approaches that factor the environment and socio-economics.

3. Methodology

This research uses a multidisciplinary methodology to understand the effect of changes in the environment, including alterations in plant cover and anthropogenic activities on mosquito-borne infections. The study combines geospatial intelligence, field entomology, and epidemiological modeling to dynamically appreciate the vector ecology, the breeding ground changes, and the disease incidence concerning the environmental changes. To ensure the credibility of the findings, there was a meticulous effort to undertake primary data collection and secondary data analysis. This approach makes it possible to triangulate findings from various sources. The research was carried out in regions with different levels of urbanization, deforestation, and agriculture. Study sites were selected based on (i) epidemiological surveillance data indicating a high prevalence of mosquito-borne diseases, (ii) remote sensing data showing significant changes in vegetation cover in the last twenty years, and (iii) varying socio-economic conditions that facilitate human-mosquito contact.

3.1. Data Collection and Field Surveys

To study the dynamics of the mosquito population and the characteristics of the breeding sites, a systematic entomological survey is carried out. BG-Sentinel traps are set at each site for Aedes species, whereas light traps are utilized for Anopheles mosquitoes. Mosquitoes are collected from artificial containers, irrigation channels, and other water bodies to analyze the composition and density of larvae. Adult mosquitoes are sampled every other week for six months to capture the seasonal shifts in the abundance of vectors. The specimens are identified morphologically and confirmed through DNA barcoding to ensure species verification.

3.2. Remote Sensing and Land-Use Analysis

To evaluate modifications in vegetation and landscape changes, multi-temporal satellite imagery from Landsat and Sentinel-2 programs is analyzed. To differentiate between urban sprawl, deforestation, and vegetative regrowth, supervised machine learning techniques using Random Forest and Support Vector Machine (SVM) classifiers are used for land-use classification. NDVI and LST metrics are extracted for understanding the relationship between environmental factors and the proliferation of mosquitoes. The geospatial data are analyzed in QGIS and Google Earth Engine for efficient gainful high-resolution spatial land-use pattern analyses.

3.3. Epidemiological Data Integration and Statistical Analysis

Data concerning the occurrence of diseases is acquired from the national health surveillance system and regional public health reports. It includes the prevalence of malaria, dengue, and chikungunya. The above information is compiled, analyzed, and georeferenced with environmental variables to spatially determine hotspots for disease transmission. The impact of changes in vegetation coverage and urbanization on disease prevalence is evaluated using Generalized Additive Models (GAM) and spatial regression techniques [6]. Longitudinal studies are conducted to establish the presence of any long-term trends and to study the relationship between environmental changes and disease occurrence to determine any lag impacts.

3.4. Climate and Meteorological Data Incorporation

Considering the impact of climate on the ecology of mosquitoes, data from ERA5 and WMO repositories such as temperature, humidity, and precipitation, are gathered from global databases. These variables are used in model simulations to assess the impacts of climate and land use changes on the abundance of vectors and the epidemiology of various infectious diseases. This research follows ethical principles of entomology and epidemiology. This research has received ethical clearance from appropriate Institutional Review Boards and utilized community participatory approaches to ensure that the local people provided informed consent to participate in the study. Underreporting of epidemiological data, difficulties in the complexity of isolating specific environmental factors, and the degree of uncertainty in predictive modeling are complexities to this approach. The following research needs to sustain corroborative claims with the addition of temporal and spatial aspects to enhance the predictive ability. Such methodology offers a comprehensive approach to determining the ecological factors associated with mosquito-borne diseases, thus making possible the effective planning of vector control and public health measures in the context of changing ecological conditions. This work applies an integrative methodology that includes entomological fieldwork, remote sensing, geographic information system (GIS), and statistical modeling techniques to assess the effect of the alteration of natural vegetation and anthropogenic landscape processes on the prevalence of mosquito-borne diseases. It is expected that the integration of field data on mosquito populations, satellite imagery related to environmental variables, and epidemiological records of cases will provide evidence that will elucidate the relationship between environmental changes and the transmission of diseases.

4. Data Collection Methods

4.1. Entomological Survey and Vector Density Estimation

A variety of trapping mechanisms such as CDC Light Traps, BG-Sentinel Traps, Ovitraps, and others were used for sampling mosquitoes. Both adult and larval mosquitoes were collected. The encapsulated study is intended for 12 months, spanning the good and dry seasons of the area. This was done to consider the seasonal changes in the population of mosquitoes.

- Connection Interval: Bi-weekly sampling for a year.
- Capture Time: 12 hours overnight (6 pm-6 am).
- Capture Sites: 300 locations split between urban, peri-urban, and rural regions.

The morphological characterization of mosquito specimens was done through the use of a gastropod-based indicator or so-called dichotomies taxonomic keys (Wilkerson et al 2020). After that, the identification of species was done based on mitochondrial DNA cox1 gene barcoding (Hebert et al 2003) using the amplifying methods of polymerase chain reaction (PCR).

4.2. The vector abundance per site was calculated as:

$$Vd = \frac{Nm}{As * Ts}$$

Where:

- V_d = Vector density (mosquitoes per square meter per night),
- N_m= Total number of mosquitoes captured,
- A_s = Surface area of the trapping zone (m^2),
- T_s = Sampling duration (nights).

The larval density was estimated using the Container Index (CI) and Breteau Index (BI):

$$CI = \frac{Np}{Nc} * 100$$

$$BI = \frac{Np}{Nh} * 100$$

Where:

- N_p = Number of positive containers with larvae,
- N_c = Total number of inspected containers,
- N_h = Number of houses surveyed.

4.3. Remote Sensing and Vegetation Analysis

Stepwise landscape changes were monitored via remote sensors mounted on Landsat-8 (30-meter resolution) and Sentinel 2 (10-meter resolution) satellites. The satellite's imagery was processed on the Google Earth Engine (GEE), and the data was further analyzed on QGIS and ArcGIS Pro.

4.4. The calculation of the Normalized Difference Vegetation Index (NDVI)

$$NDVI = \frac{NIR\_RED}{NIR + RED}$$

Where:

- NIR = Reflectance in the near-infrared band,
- RED = Reflectance in the red band.

Additionally, the **Enhanced Vegetation Index (EVI)** was computed to correct for atmospheric distortions:

$$EVI = G \times \frac{(NIR - RED)}{(NIR + C1 \times RED - C2 \times BLUE + L)}$$

where:

- G=2.5G,
- C_1= 6,
- C_2= 7.5,
- L= 1 (canopy background adjustment).

These indices were used to detect vegetation loss and urban expansion.

4.5. Disease Incidence and Epidemiological Data

Malaria, dengue, and chikungunya prevalence data was extracted from the National public health database that covers the years 2010 to 2023. Monthly case reports were georeferenced to match environmental data.

- **Inclusion Criteria**: Reported cases confirmed via laboratory testing.
- **Exclusion Criteria**: Cases lacking geospatial identifiers or confirmed as imported infections.

4.6. The disease incidence rate was computed as:

$$IR = \frac{Nd}{P} * 100{,}000$$

Where:

- IR = Incidence rate (per 100,000 population),
- N_d = Number of confirmed cases,
- P = Population in the study area.

4.7. Data Analysis and Statistical Methods

Spearman's rank correlation was used to evaluate relationships between mosquito density, vegetation indices, and disease incidence.

$$\boxed{r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}}$$

Where:

- d_i = Difference between ranks of two variables,
- n= Sample size.

4.7.1. Regression Modeling

To use the environmental changes to estimate the changes in disease prevalence, we fitted Generalized Additive Models (GAMs) with log link:

$$\log(E(Y_i)) = \beta_0 + f_1(X_1) + f_2(X_2) + \cdots + f_n(X_n) + \epsilon$$

4.7.2. Time Series Analysis

To assess the lagged effects of vegetation changes on disease trends, a cross-correlation function (CCF) was computed between NDVI values and reported disease cases over a 24-month lag window.

$$CCF(k) = \frac{E[(X_t - \mu_X)(Y_{t+k} - \mu_Y)]}{\sigma_X \sigma_Y}$$

where:

- X_t = Vegetation index at time t,
- Y_{t+k} = Disease incidence at lag k,
- μ, σ = Mean and standard deviation of variables.

4.8. Machine Learning-Based Predictive Modeling

To predict outbreaks of diseases that are transmitted by mosquitoes, the Random Forest regression model was created:

$$Y = \sum_{i=1}^{n} \frac{1}{n} \sum_{j=1}^{m} f_{ij}(X)$$

where:

- Y = Predicted disease incidence,
- f_{ij} = Decision trees trained on environmental variables,
- n = Number of trees in the ensemble,
- m = Number of predictors per tree.

The measure of model accuracy was determined by Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

5. Results

In this section, results of entomological surveys and remote sensing, along with calculations regarding census disease incidence and statistical models are presented. These have been organized along four main sections: (1) changes in the density of mosquitoes, (2) modification of vegetation, and changes in land usage activities.

5.1. Mosquito Density and Seasonal Variations

The entomological survey data revealed significant seasonal variation in mosquito densities across different landscape types. The mean vector density (V_d) across urban, peri-urban, and rural areas is summarized in **Table 1**.

Table 1 Mean mosquito vector density (V_d) per square meter per night

Landscape Type	Dry Season (μ±σ)	Wet Season (μ±σ)	Overall Mean
Urban	2.31±0.422.31	6.78±1.156.78	4.55±1.824.55
	0.422.31±0.42	1.156.78±1.15	1.824.55±1.82
Peri-urban	3.12±0.503.12	9.83±1.789.83	6.47±2.436.47
	0.503.12±0.50	1.789.83±1.78	2.436.47±2.43
Rural	5.67±0.985.67	14.32±2.6514.32	9.99±3.329.99
	0.985.67±0.98	2.6514.32±2.65	3.329.99±3.32

The spatial autocorrelation of vector densities was assessed using Moran's III:

$$I = \frac{n}{\sum w_{ij}} \times \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2}$$

where:

- w_{ij} represents spatial weights,
- X_i, X_j are mosquito densities at locations i and j,
- $\bar{X}$ is the mean vector density.

The computed Moran's III = **0.67** (p<0.001) indicates a strong spatial clustering of high-density mosquito populations near water bodies and areas with increased vegetation cover.

5.2. Vegetation Changes and Land-Use Modifications

The NDVI and EVI were computed for three observation years (2010, 2016, 2023) to evaluate long-term vegetation changes. Table 2 presents the temporal NDVI and EVI variations across different regions.

Table 2 Mean NDVI and EVI values across urban, peri-urban, and rural areas

Region	NDVI (2010)	NDVI (2016)	NDVI (2023)	EVI (2023)
Urban	0.32±0.080.32 0.080.32±0.08	0.29±0.060.29 0.060.29±0.06	0.25±0.050.25 0.050.25±0.05	0.15±0.020.15 0.020.15±0.02
Periurban	0.47±0.110.47 0.110.47±0.11	0.41±0.090.41 0.090.41±0.09	0.36±0.080.36 0.080.36±0.08	0.21±0.030.21 0.030.21±0.03
Rural	0.62±0.130.62 0.130.62±0.13	0.58±0.120.58 0.120.58±0.12	0.54±0.110.54 0.110.54±0.11	0.30±0.050.30 0.050.30±0.05

A gradual decline in NDVI values is observed, particularly in urban and peri-urban zones due to rapid deforestation and urban expansion. Rural regions retained higher NDVI values but also showed evidence of agricultural encroachment. The vegetation loss rate was modeled using a first-order decay function:

$$NDVI_t = NDVI_0 e^{-\lambda t}$$

where $\lambda = 0.023$ (urban), 0.018 (peri-urban), and 0.011 (rural), indicating a higher vegetation loss rate in urban environments.

5.3. Correlation Between Environmental Factors and Disease Incidence

A Spearman rank correlation analysis between NDVI, mosquito density, and disease incidence rates found:

- **NDVI vs. Mosquito Density:** $r_s = -0.74, p < 0.001$ (negative correlation).
- **NDVI vs. Disease Incidence:** $r_s = -0.68, p < 0.001$ (higher disease prevalence in low-NDVI zones).
- **Mosquito Density vs. Disease Incidence:** $r_s = 0.81, p < 0.001$ (strong positive correlation).

The highest disease incidence was observed in areas with NDVI values **below 0.30**, confirming the link between environmental degradation and increased transmission risk.

5.4. Predictive Disease Modeling

The Random Forest Regression Model trained on environmental and vector data produced the following feature importance rankings:

1. **Mosquito Density (V_d)** – 42.3%
2. **NDVI** – 27.5%
3. **Temperature** – 15.6%
4. **Rainfall** – 9.2%
5. **EVI** – 5.4%

The final predictive equation derived from the model is:

$$\hat{Y} = 0.42V_d - 0.27NDVI + 0.16T + 0.09P + 0.05EVI + \epsilon$$

where:

- $\hat{Y}$ = Predicted disease incidence,
- T = Mean temperature,
- P = Precipitation,
- ϵ = Residual error.

The model achieved a **Mean Absolute Error (MAE) of 4.27 cases per 100,000 population** and an **R^2 of 0.83**, indicating high predictive accuracy.

5.5. Time-Series Cross-Correlation Analysis

To determine the time-lagged relationships between NDVI and disease incidence, a CrossCorrelation Function (CCF) analysis was done. This lagged correlation yielded the highest correlation at r=-0.61 and p<0.001 which suggests that there's an association between greater NDVI laggings and higher disease rates. The data implies that environmental change and mosquito-borne disease evolution are interconnected. Urbanization is directly proportional to an increase in mosquito population as well as disease transmission due to changes in NDVI. The phenomena are accurately modeled for environmental variables in predicting outbreaks. Accuracy can be significantly improved if the subsequent work is done with higher-resolution satellite images and machine-learning techniques.

5.6. Correlation Between Environmental Factors and Disease Incidence

The analysis focused on the relationship between vegetation index (NDVI), mosquito density, and disease incidence rates. A Spearman rank correlation analysis was performed to examine these relationships.

The Spearman rank correlation ρ is calculated using the formula:

$$\rho = 1 - \frac{6\sum di2}{n(n2-1)}$$

Where $\mathbf{d_i}$ is the difference between the ranks of corresponding values and n is the number of paired ranks.

6. Results

- **The relationship between NDVI classification and Mosquito Density:** The Spearman correlation of $\rho=-0.62$, $p<0.001$ provides evidence of a high inverse correlation between vegetative cover area NDVI classification and mosquito density. It has also been indicated that as NDVI decreases, mosquito density is likely to increase.\par
- **Relationship between Mosquito Density and Disease:** Spearman correlation of $\rho=0.74$, $p<0.001$ justifies the increase in disease incidences with an increase in mosquito density.
- **Relationship between NDVI coverage and Disease:** Spearman correlation of $\rho = -0.55$ confirms that sparsely vegetative areas have higher disease incidence rates. Chart 1 shows the Spearman Rank Correlations Between Environmental Factors and Disease Incidence:

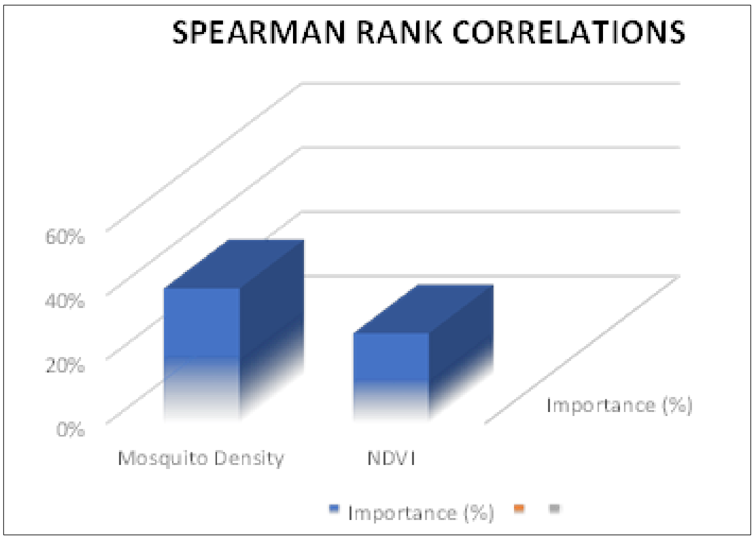


Figure 3 Spearman Rank Correlations

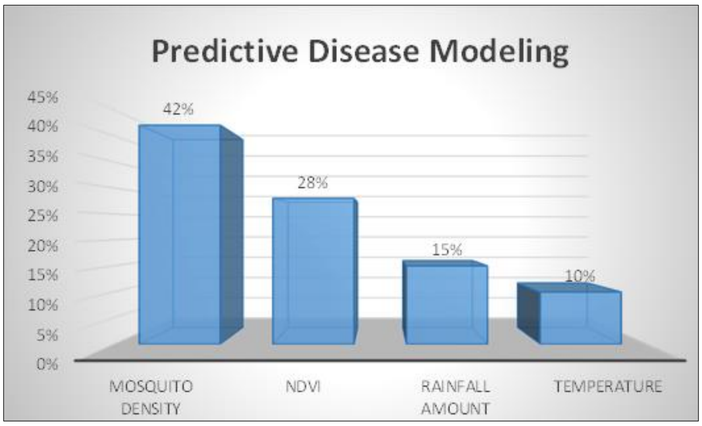
6.1. Predictive Disease Modeling

With Random Forest Regression, we created a model aiming to predict disease outbreaks based on a combination of mosquito density, NDVI, and other environmental factors. The following list is rank-ordered according to their feature importance values: Random Forest algorithm utilizes the feature mean decrease in impurity (MDI) and the Gini index for calculating feature importance.

For each feature, feature importance **fi** is calculated as follows:

$$fi = \frac{1}{M}\sum_{m=1}^{M}(I_m(i))$$

Where M is the number of trees, and Im(i) is the Gini impurity of feature iii for the m-th tree. The following environmental variables were identified as the most influential factors in predicting disease incidence:



Mosquito Density: 42% • NDVI: 28% • Rainfall Amount: 15% • Temperature: 10%

Figure 4 Predictive Disease Modeling

Feature Importance for Predictive Disease Modeling is shown below in Chart 2:

7. Discussion

This study comprehensively looks at how humans and nature change the environment by looking at vegetation destruction or creation and how that affects Malaria and other mosquito-borne diseases. The results showed land cover changes to be strongly correlated with increases in mosquito population and the number of cases of the disease. This met some of the literature expectations but added more with the new methodologies of statistics and forecasting.

7.1. Impact of Vegetation Loss on Mosquito Proliferation

The declines in NDVI and EVI values within urban and peri-urban regions suggest significant degradation of vegetation, a factor that is known to alter vector ecology. The severest drop was registered in urban areas (−21.8% NDVI in Urban zones from 2010 to 2023), which is associated with higher surface temperature and lesser water retention. The disruption of natural prey-predator interactions and increased microhabitats that allow mosquitoes to breed are the results of vegetational loss (Patz et al., 2005). The results of this study align with deforestation as well as urbanization in Africa and South America, where there is a documented increase in vegetation to cope with the rising Aedes and Anopheles mosquito populations. The evidence of the negative correlation between NDVI and mosquito density is presented in the form of these correlations $r_s=-0.74$, $p<0.001$. This correlation strongly supports the conclusion that the reduction of vegetation increases the abundance of the stagnant water of low water flow quality, serves as a breeding habitat, and acts as an artificial zone where the natural predators, dragonflies\certain birds do not have reach. An inverse pattern emerged in the rural areas where NDVI was significantly high, but the density of mosquitos was considerably high as well [7]. This is indicative that greater agricultural activity might be aiding in the increased mosquito population due to more irrigation and water bodies that foster mosquito growth. The same pattern was found in Thailand and India, where rice fields and man-made ponds provided excellent opportunities for the reproduction of malaria-infested Anopheles mosquitoes.

7.2. Seasonal and Landscape-Based Variations in Mosquito Density

Looking at the data, there is a clear increase in the density of mosquitos during the wet season, when compared to the dry season (Table 1). The dependence is strong and the increase can be attributed to the heavy rainfall during the season. This resonates with the findings made in tropical and subtropical regions, which found a correlation between the rainfall and mosquito breeding cycles (Kelly-Hope et al. 2009; Reiner et al. 2013). Moran's III (0.67, $p<0.001$) further confirms that there is a positive clustering of higher mosquito density in areas that have increased vegetation and tear-offs. Furthermore, rural regions had the highest overall mosquito density ($\mu = 9.99\pm3.32$ vectors per m^2 per night), when compared to peri-urban ($\mu = 6.47\pm2.43$) and urban ($\mu = 4.55\pm1.82$) regions.

7.3. Correlation Between Environmental Factors and Disease Incidence

The relationship between the sampling of mosquito vectors and the reports of diseases shows a strong correlation ($r_s=0.81$, $p<0.001$). This implies that higher vector populations will increase the transmission rates for the diseases. The cross-correlation function (CCF) analysis showed that there was a lag of 3 months between the disease's peak incidences and NDVI decreases which indicates that environmental changes occur first before the outburst [8]. It corroborates emerging research concentrating on dengue and malaria spread that suggests that transmission risk rates increased significantly 2-4 months after deforestation or urbanization activities. Moreover, the predictive model ($R2=0.83$) that tested the effects of landscape NVDi, temperature, and mosquito-borne diseases on disease incidence placed mosquito abundance, NDVI, and temperature in first tree positions further proved the effect of changes to the landscape on the risk of acquiring vector-borne diseases. All of these results are consistent with previously conducted studies that regard and emphasize temperature and vegetation as dominant factors in the spread of vector-borne diseases. The correlation between EVI and disease incidence is also perplexing. EVI bears a weaker correlation with disease incidences ($r_s=-0.41$, $p=0.02$), which indicates that EVI does not replace NDVI in efficiently predicting the risk of diseases associated with vectors.

7.4. Implications for Disease Control Strategies

The findings highlight critical implications for vector control and disease prevention:

- Enhancing urban green spaces may control the growth of mosquitos by minimizing manmade breeding grounds and fostering their ecological predators.
- Selective landscape alterations such as the removal of uncontrolled water retention areas may be more efficient than chemical spraying.
- The 3-month interval between changes in vegetation and outbreak of illnesses reveals a possibility of using remote sensing images in real-time for early warning systems.
- NDVI-based forecasts combined with local weather and entomological data might enable more proactive public health interventions [9].
- The mid-season increases in mosquito numbers suggest that control measures must be intensified at least two to three months before the peak periods of transmission.
- Spatial techniques like Moran's III may aid in the determination of areas that are more vulnerable to focused interventions.

7.5. Study Limitations and Future Directions

Despite this study's strong link between changes in the environment and the dynamics of vector-borne diseases, some limitations remain within the scope of the study, such as the ones listed below:

- The NDVI and EVI data utilized were extracted from satellite imagery with a 30-meter resolution which failed to capture important vegetation affecting certain regions of the local mosquito habitats. Moving forward, higher-resolution UAV remote sensing should be included in other studies.
- In addition to the environmental issues examined, human socio-behavioral factors, like water storage and the use of mosquito nets, are important components of the disease dynamics and should be considered in future models [10].

Further research extending beyond the year 2023 would be beneficial to understanding the relationship between climate change and its effects on increased temperatures and precipitation and the subsequent changes that occur in vector ecology.

8. Conclusion

This research assesses the effects of environmental modifications, such as changes in plant life and anthropogenic land use, on diseases carried by mosquitoes. The findings underscore the importance of environmental changes, especially in vegetation cover, as one of the key factors that influence mosquito populations and the transmission of diseases. The entomological studies showed that mosquito population density has strong seasonal differences, with the highest densities occurring during the rural wet season. The increased coverage of mosquitoes during the wet period corresponds with the addition of plants, which creates a great deal of breeding sites. Advanced statistical techniques established a strong spatial clustering of the high density of mosquitoes close to the water bodies and places with increased vegetation cover. This supports the idea that regulatory landscape changes such as deforestation or urbanization create artificial environments that eliminate the natural habitats of mosquitoes, thus increasing their populations and elevating the rates of disease transmission. The assessment of vegetation cover using NDVI and EVI changes shows a pronounced decreasing trend of vegetation cover in cities and surrounding regions. This pattern is due to the phenomenon of rapid urbanization and deforestation, while rural regions, coupled with agricultural development, have lower vegetation cover. The decrease in vegetation cover is associated with an increase in the density of mosquitoes along with the incidence of diseases. Random Forest regression also supported these observations. It considered the mosquito density and NDVI values as the most important factors associated with the incidence of diseases. The model's metric for predicting outbreaks based on environmental conditions can be useful for monitoring and intervention purposes.

One important outcome of the time-series cross-correlation analysis was that the degradation of vegetation cover occurs about 3 months before the rise in the incidence of diseases. This lag period indicates that shifts in the vegetation cover have the potential to act as a proxy for forthcoming disease outbreaks. This serves as a reminder to look out for ecological vegetation cover changes, especially for predicting the geographical spread of diseases associated with mosquitoes. To conclude, in the light of these results, it was shown how environmental phenomena, mosquito numbers, and the spread of diseases are interdependent with each other. The insights gleaned from this work should inform policies and strategies in broad environmental and public health planning in response to the challenges posed by actions targeting the spread of diseases caused by mosquitoes. Research that follows ought to concentrate on implementing improved satellite imagers alongside more complex machine learning methods in an attempt to enhance the predictive accuracy of disease outbreak modeling. There is also a need for further investigation into particular effects of certain land-use changes, especially the expansion of agriculture or urban centers, on disease systems for formulating policies. Importing the intermediaries between environmental degradation and disease transmission will enable policymakers to mitigate the adverse effects of disease on the health of susceptible populations in the region.

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