Spatiotemporal dynamics and environmental drivers of the 2022-2024 dengue outbreak in Nepal

Government of Nepal
Nepal Health Research Council (NHRC)
Ramshah Path, Kathmandu, Nepal

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Acknowledgement

I am pleased to publish the report of study entitled *Spatiotemporal Dynamics and Environmental Drivers of the 2022–2024 Dengue Outbreak in Nepal.* Dengue is a rapidly emerging vector-borne disease with significant public health implications, causing seasonal outbreaks that place substantial burden on health systems. Understanding the patterns, drivers, and spread of dengue is essential for evidence-based policy-making, strategic planning, and effective implementation of prevention and control measures. This study provides critical insights that can inform national and local strategies for outbreak preparedness, vector control, and public health interventions in Nepal.

Upon the successful completion of this study, I would like to express my gratitude to Dr. Meghnath Dhimal, Chief of the Research Section at the Nepal Health Research Council, for his valuable scientific input from the inception to the completion of this work.

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Executive summary

Dengue incidence has risen significantly in Nepal in recent years, posing an escalating public health challenge. Understanding the spatial distribution of cases and the environmental drivers that shape transmission is essential for guiding effective control measures and targeted intervention strategies. In this study, we utilized publicly available environmental and socioeconomic geospatial covariates sourced from multiple geoportals, alongside monthly dengue case data extracted from situation reports published by the Epidemiology and Disease Control Division (EDCD), Government of Nepal.

We first characterized the spatiotemporal dynamics of the outbreak and mapped spatial patterns using Global Moran's I and Local Indicators of Spatial Association (LISA) to identify statistically significant clustering. Subsequently, we applied a Random Forest (RF) machine learning model to predict case distribution and assess associations between dengue incidence and geographic covariates.

The results revealed heterogeneous spatial distribution of dengue cases across the study years, with significant clusters emerging in different regions of the country. Monthly patterns showed sporadic and spatially unstructured distribution until June, followed by a sharp rise from July, peaking in September, and declining thereafter—producing statistically significant monthly clusters. The RF model indicated that districtlevel spatial variation was primarily driven by urban related environmental factors, including road density, nighttime lights (NTL), and the Human Footprint Index, along with precipitation. In contrast, temperature played a comparatively minor and variable role across outbreak years.

These findings provide important insights for designing spatially targeted dengue control and intervention strategies in Nepal.

Contents

1. Introduction

Dengue fever is mosquito-borne viral disease widely distributed in tropical and subtropical countries across the world. *Aedes aegypti and Aedes albopictus* are primary mosquito vectors responsible for dengue transmission [1]. It has been an important public health concern worldwide, with 400 million infections each year (WHO) [2], and significant death. It is widely distributed in tropical countries around the world with reports from more than 128 countries [3] and is continuously expanding in previously unaffected regions of Europe and Americas. Approximately 4 billion people are at risk of dengue infection worldwide [4]. Factors such as global climate change, increased human mobility and rapid urbanization, expected to contribute to the continued geographic spread and rising incidence of dengue in the coming year [5–7]. Despite the growing impact there are still no effective vaccines or specific treatment available to stop the rapid worldwide spread of dengue fever [8]. As such, deeper understanding of the dengue transmission dynamics and spatial distribution patterns is essential to for developing effective control and intervention strategies.

The spatiotemporal dynamics of dengue are complex and influenced by several factors. Temperature plays a crucial role in the survival, growth and development of mosquito vectors in different ways. Higher temperature alters vectorial capacity, vector competence and extrinsic incubation period [9,10]; however, extreme temperatures are negatively associated with the disease transmission [6]. Additionally, low winter temperature of 16 and 36 °C significantly reduce adult mosquito longevity and female fecundity [11]. Additionally, low winter temperatures are a key limiting factor for survival of *Ae. aegypti eggs* in the environment [12].

Rainfall provides the suitable habitat for the reproduction, early growth and development of immature mosquitoes. However, extreme rainfall can wash away out the eggs and larvae leading to a reduction in mosquito density, thereby affecting dengue transmission negatively. In addition to climate factors, socioeconomic conditions also play an important role in the spread of dengue. Rapid and unplanned urbanization has been attributed to increased risk of dengue transmission in many places. Lower socioeconomic status and higher population density has also been linked positively with dengue transmission. The influence of urbanization, population density, GDP and vegetation on dengue transmission has been widely documented. Understanding how these factors affect spatial distribution patterns is essential to understanding spatial dynamics and resulting patterns of disease spread. The use of geospatial analytics in study of infectious diseases like dengue, has been rapidly increasing recently. It has been a powerful tool to visualize disease distribution, detect disease clusters, and explore spreading patterns[13]. Understanding such dynamics is not only important for guiding effective interventions and timely action but also for strengthening surveillance and building an early warning system. The rapid evolution of machine learning techniques provides additional opportunities to identify the spatial drivers that facilitate the spread of disease. These tools are especially valuable for detecting in large and complex datasets. Such methods have proven useful tools to predict distribution of disease, identify the important drivers that shape the distribution patterns and to seek the nonlinear association which is important not only for the place specific control intervention but also can play a vital role to strengthen the disease surveillance and supporting the development of robust early warning system.

Since report of first dengue case in 2004 [14], Nepal has experienced several dengue outbreaks, notably in 2006, 2010, 2013, 2019, 2022,2023 and most recently in 2024 [15]. Of them, the 2022 outbreak was the most severe, accounting for more than 50% of all dengue cases reported in the country since the disease was first documented. This outbreak was not only the largest in scale, but also exhibited higher severity and hospitalization rates than in the past, largely due to the co-circulation of multiple dengue virus serotypes (DENV-1, 2, and 3) [16]. For the first time, dengue cases were reported across all 77 districts and seven provinces of Nepal. The 2023 and 2024 were also big outbreak. Therefore, detailed understanding of the spatiotemporal dynamics and influencing factors is necessary to inform the effective prevention and control strategies for potential future outbreaks.

Despite the increased risk of infection and frequent outbreaks in the recent years, little is known about the spatial process and resulting distribution patterns of dengue in Nepal. Understanding environmental and socioeconomic drivers and their association is important for informing effective control and intervention policies. Although a few previous studies attempted to map the spatial distribution of disease incidence [17,18], predict the potential impact of climate change on the future distribution [19], Identification of key drivers[20] or characterize the spatiotemporal dynamics of the recent outbreaks [13], a comprehensive spatially explicit scientific national level study based on recent outbreak data is still lacking. As a result, several important questions remain unanswered: What were spatial distribution patterns of dengue during the 2022, 2023 and 2024 outbreaks? How did these patterns evolve throughout different months of outbreak seasons in recent years? Which environmental or socioeconomic factors have driven the outbreaks? And do these driving factors differ across outbreak years?

For this analysis, we used freely available monthly dengue case data aggregated across 77 districts of Nepal obtained from the situation report of the EDCD. Environmental variables were compiled from open -access geoportals. Our methodology included two main components. First, we used exploratory spatial analysis using Global Moran's I to assess spatial dependency on the in-dengue case distribution and identified district -level disease clusters through the Local Indicators of Spatial Association (LISA) approach. Secondly, environmental and socioeconomic factors on dengue incidence were analyzed using a machine learning Random Forest model.

2. Materials and Method

2.1 Study area

Nepal is located in the southern side of the central Himalayas between China and India at 26^0 to 30^0 latitudes north and 80^0 to 88^0 longitudes east (Figure: 1). There are remarkable differences in land topography where elevation ranges from 60 m to 8848m within a shorter than 200 km latitudinal extent. Based on the elevation and land topography, Nepal is divided into five major physiographic zones- Tarai (below 600 m), Siwalik (100-2000 m), Hill (200-3500 m), Middle Mountain (700-4100 m) and High Mountain (1800-8800 m) [21]. Nepal's climate is broadly classified as subtropical monsoon characterized by distinct seasonality in temperature, precipitation, and humidity. The country experiences four distinct seasons: winter (December of the previous year, through February), pre-monsoon (March-May), monsoon (June– September), and post- monsoon (October and November) [22]. Due to its extreme variation in altitude and topography, Nepal encompasses a diverse range of bioclimatic zones. These topographic orientation and climatic variations have a great impact on population distribution, development infrastructure and on the distribution of pathogens and vectors across the country.

2.2 Data Source

Dengue is a notifiable disease in Nepal, which is reported to the EDCD via the Early Warning and Reporting System (EWRS) on a weekly basis. The EWARS is a hospital-based sentinel surveillance system currently operational in 118 hospitals throughout Nepal. The EDCD publish the situation report with district- level aggregated disease count on monthly basis using the EWARS report. The report is further adjusted using data from the Surveillance Outbreak Response Management and Analysis System (SORMAS) and an offline line listing file. We used monthly aggregated data extracted from the situation report published by EDCD, Government of Nepal, which is publicly available from the EDCD portal (https://edcd.gov.np/). The district polygon spatial file was retrieved from the National Spatial Data Clearinghouse (https://nationalgeoportal.gov.np/#/login). We also collected several environmental and socioeconomic drivers that can influence the transmission dynamics of dengue. First, we collected dynamic variables synchronizing the outbreak year, which were precipitation, NDVI and LST. Mean annual Precipitation data for all three years were retrieved from GPM IMERG (GPM_3IMERGM)[23] based on monthly precipitation product with a spatial resolution of 11 km, we downloaded this dataset from the Online Visualization and Analysis Infrastructure (Giovanni) system in the NASA Goddard Earth Science Data and Information Service Center (GES DISC) (https://giovanni.gsfc.nasa.gov/giovanni/). Land Surface Temperature (LST) and NDVI were also collected for all the outbreak years. We used MOD11A2 [24] product for LST which is a monthly product with 1 km spatial resolution of MODIS earth observation. Similarly, for the NDVI we retrieved MOD13A product, which is also a monthly averaged NDVI product with 1 km spatial resolution[25]. We automatically downloaded these both product (NDVI, LST) for all 12 months of each outbreak year using the MODIStsp [26] package directly in R. The full list of environmental drivers considered in this analysis is given in the table 1.

Table 1: The List of Potential Environmental and Socioeconomic Drivers of the 2022 Outbreak

	Year	Variables	Resolution	Unit
Dynamic Variables	2022	Land Surface Temperature	1km	Degree Centigrade
	2022	Precipitation	11 km	Milliliter (mm)
	2022	NDVI	1km	Index (0-1)
Static Variables	2016	Night Time Light	1km	nanoWatts/cm2/sr *1E9
	2020	Population count	1 km	Person/pixel
	2018	Road density	5km	Km/km^2
	2020	POI density	100 m	No of POI/ km^2
	2020	Building density	100m	No of buildings/ km^2
	2020	Proportion of Urban Area	100m	Percent
	2016	Human Footprint	1km	Index

In addition, we also collected several other variables that can influence the transmission dynamics of dengue, different open geoportals may not synchronized with the outbreak year but can be used for the nearest year due to their static influence. The grided population density was retrieved from worldpop (https://hub.worldpop.org/) in 1 km spatial resolution for the year 2020. Similarly, we collected road density data from the Global Roads Inventory Project's global roads database (https://www.globio.info/download-grip-dataset) in 5 arc minutes spatial resolution [27]. Many different open -sources road databases, including Open Street Map, were used to compute the road density for the entire globe. The UNSDI-Transportation data model was applied for harmonization of the individual source datasets. POI density and building density were computed based on the POI and building data sourced from the open street map (https://www.openstreetmap.org/). The open street map data was downloaded via Geofabrik open street data portal (https://www.geofabrik.de/). The POI data is point data on real geographical entities, with spatial and attribute information. Human Foot Print index was extracted from te NASA Socioeconomic Data and Applications Center (https://sedac.ciesin.columbia.edu/). Finally, the proportion of urban areas was computed based on the landcover data accessed from ICIMOD data portal (https://rds.icimod.org/Home/Index) and For NTL, VIIRS Annual Night Time Lights version 2 (VNL v2) dataset [28] was. We utilized the median product for the year 2020. The NTL is a widely used proxy related to human activities such as pop density, wealth and urbanization.

All variables were harmonized in terms of spatial resolution and extent using the 'sf' and 'terra' packages in R. Finally, the mean values of these predictor variables were extracted using the district-level shapefile retrieved from the National Spatial Data Center (https://nationalgeoportal.gov.np). The zonal mean values for all 77 districts were linked with monthly and annual mean dengue cases and used for further analysis.

2.3 Analysis

Spatial Autocorrelation Analysis

Initially, we conducted spatial autocorrelation analysis to explore the spatial distribution patterns of the outbreak. Spatial autocorrelation quantifies the extent to which the values of a variable exhibit correlation in space. Our focus was to determine whether dengue cases were clustered together, dispersed, or randomly distributed across Nepal during the recent outbreak. To achieve this, we employed both Global Moran's I and its local version.

We computed global spatial autocorrelation using Moran's I index. We did this for all the months of the selected years (2022, 2023, 2024) and the average annual incidence of all the outbreak years. Moran's I is a widely used spatial autocorrelation method to describe the extent to which a variable is correlated with itself through space[29]. The Moran's I coefficient range between [−1, 1], and the specific explanation is that the spatial distribution into clustered ($I > 0$), random ($I = 0$) and discrete ($I < 0$). In other words, Positive spatial autocorrelation occurs when observations with similar values are closer together (i.e. clustered). Negative spatial autocorrelation occurs when observations with dissimilar values are closer together (i.e. dispersed). We chose first order queen continugity to define a spatial weight matrix, and analysis was done using geodata software. Mathematically, Moran's I can be expressed as :

$$I = \frac{n \sum_{i=1}^{n} wij(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} w_{ij} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})^2} \quad ....(1)$$

Where I is the global Moran's I index X_i and X_j are the reported dengue cases, of W_{ij} is the spatial weight matrix (i ≠j) represents the mean n represents number of districts

We also wanted to analyze differences in spatial autocorrelation and map the spatial distribution patterns quantitatively. To achieve this, we utilized the Local Moran's I statistic, commonly known as LISA (Local Indicators of Spatial Association)[30]. It evaluates whether nearby observations have similar values or not. Unlike global Moran's I, which provides a single measure for the entire dataset, Local Moran's I calculates spatial autocorrelation for each location, allowing for the identification of local clusters of similarity or dissimilarity. It effectively identifies clusters exhibiting high-high (HH) or low-low (LL) values, along with outliers or areas displaying high-low (HL) and low-high (LH) value combinations. HH can be considered spatial hot spots and LL cold spots, while the latter two categories are spatial outliers. Local Moran's I statistics is expressed by Anselin [30]is as follows:

$$I_i = (x - \bar{x}) \sum_{i=1\ j \in ji}^{n} w_{ij} \left(x_j - \bar{x}\right) \text{...........}(2)$$

Where ji represents neighborhood in I region; j represents only the neighboring ji and the the mean of neighborhood observation. Both the Local and global versions Moran's I was computed in GeoDa open-source software. The computation was permuted 999 times, and a significance filter was set to .05. First order Queen's contiguity weight matrix was chosen to define the spatial relationship.

Random Forest Regression

We used random forest regression to model the relationship between reported dengue cases and environmental variables that influence the spatial variability and heterogeneity of the recent 3 -year outbreak. Random forest being resilient to overfitting, capable to provide nonlinear relationship and high predictive power [31], has been is popular and widely used machine learning technique to in the study of various infectious disease research.

Random forest builds multiple decision trees which are known as a forest and glues them together to urge a more accurate and stable prediction. The decision trees are generated based on bootstrap sample (bagging). In this process 2/3 data is used to fit the model, leaving the 1/3 of data which is called out of bag. The out-of-bag data is used for the validation and in the computation of variable importance. The average prediction of all computed trees is used as the final output. We fitted three different models using the mean annual incidence of each outbreak year of 2022, 2023, and 2024. The purpose was to assess the explanatory power of RF in different outbreak years.

There were 10 variables as predictors. Before fitting the final model, we selected the most influential variables using the recursive feature elimination (RFE) procedure and dropped less influential variables. This method works by iteratively removing the least important variables from the set of predictors until the predictive performance is the highest. For this we chose fivefold cross validation approach and the random grid search method was applied.

To evaluate model performance, we choose most widely used metrices: the coefficient of determination (R-squared), mean absolute error (MAE) and the root mean square error (RMSE) based on the 5-fold cross validation [32] using the predictor variables obtained from recursive feature elimination. The larger the R-squared (R2) and the smaller the RMSE and MAE indicates the best model prediction. In the cross-validation process, the validation data were divided into 5 parts. The whole process was iterated 100 times, and in each iteration, 4 parts were used for training and the remaining part for testing. The average performance metrics of the 100 iterations are reported as the final performance score of the models. Mathematically, these metrices can be expressed as:

$$R^2 = \frac{\sum_i^n (P_i - \bar{O})^2}{\sum_i^n (M_i - \bar{O})^2} \ldots\ldots\ldots\ldots\ldots (3)$$

$$RMSE = \sqrt{\frac{\sum (P_i - O_i)^2}{N}} \ldots\ldots\ldots\ldots\ldots (4)$$

$$MAE = \frac{1}{N} \sum |P_i - O_i| \ldots\ldots\ldots\ldots\ldots (5)$$

Where O is observed dengue cases, P is the predicted cases, is the mean of observed cases and n is the number of samples in the validation set.

Variables importance was assessed to determine which variables had the strongest influence on the spatial distribution of dengue incidence in Nepal. The importance was measured as the standardized increase in mean square error (MSE) after random permutation of the covariate values from OBB data. The most important variables produce the largest increases in MSE error when permuted[33]. A high importance of a variable indicates that the RF model relied heavily on a specific variable during the model fitting process. It is a common metric to compare the relative influence of predictor variables and statistical analysis were done the 'random forest', 'dismo' and 'caret' package in R. Partial dependence plots (PDD) were employed to visualize the individual effects of each predictor variable on the response variables, while controlling for the average effects of all other variables in the model. Both models were utilized to generate predictive maps of dengue distribution at the district level for both the peak month and the entire outbreak year. These predictions were subsequently compared with observed dengue incidence maps for September and the entire outbreak year to assess predictive performance. All modelling, and statistical analyses were conducted using the 'randomForest', 'dismo', and 'caret' packages in R.

3. Results

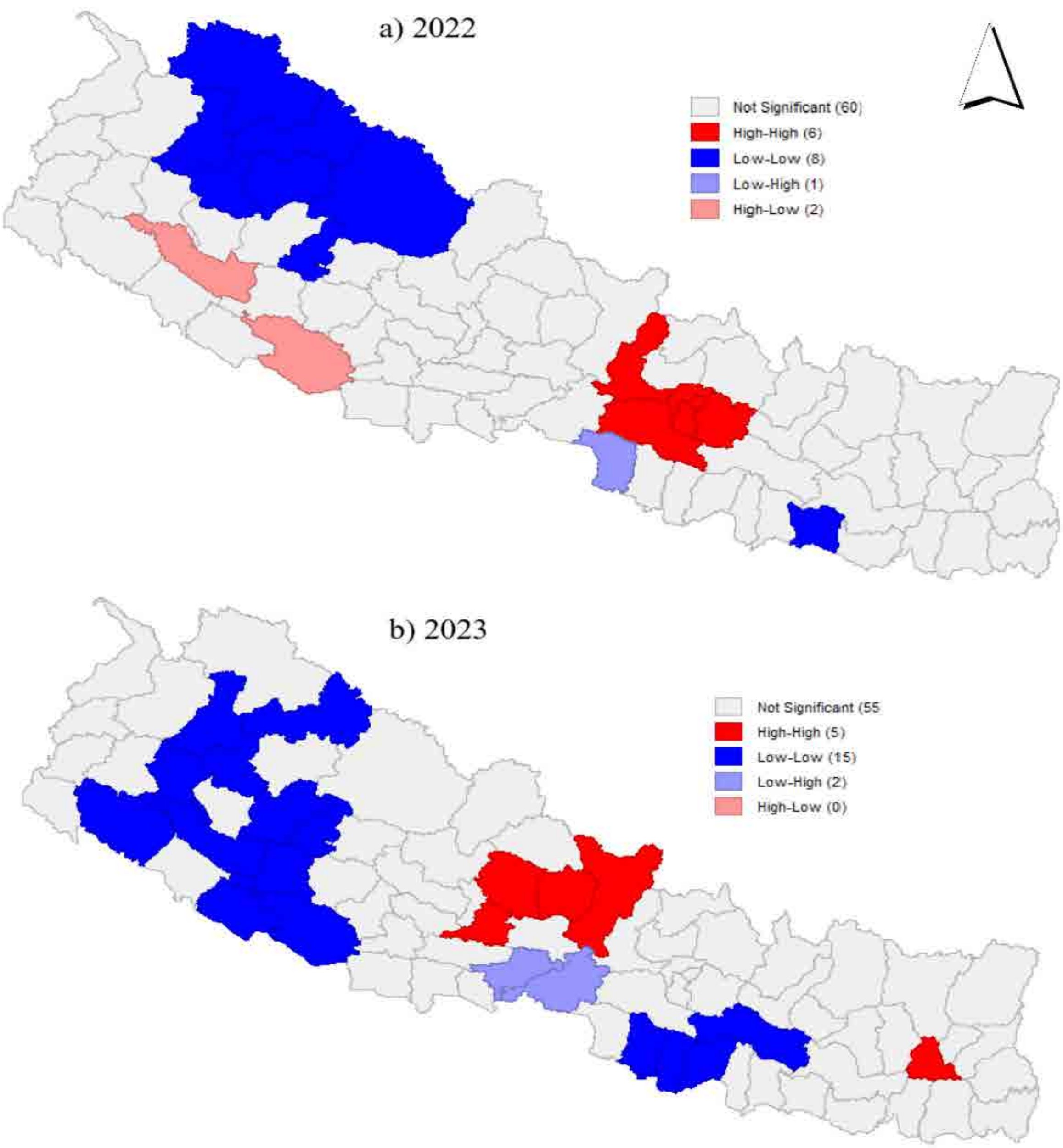
3.1 Spatiotemporal patterns of dengue outbreak (2022-2024)

A total of 140,412 laboratory confirmed dengue cases were reported during the outbreaks in Nepal over the past three years, accounting for approximately 85 % of total cases ever recorded in the country. Among these, 2022 had the highest number of reported cases, followed by 2023 and 2024. The global Moran's I (Table 2) reveal statistically significant positive spatial autocorrelation in the mean annual distribution of dengue incidences in all three outbreak years with varying levels of heterogeneity. The spatial dependency was strongest in 2022 compared to the other two years, while the distribution in 2024 was more homogenous. Nonetheless even in 2024 dengue incidences at the district level exhibited nonrandom spatial pattern (Table 2).

Table 2: Global Moran's I over different outbreak years

Year	Total Dengue cases	Moran's I	Z score	P value
2022	54,784	0.452	8.3131	0.010
2023	51,243	0.120	1.9056	0.040
2024	34,385	0.332	6.1813	0.015

The LISA map illustrated the spatial distribution patterns of dengue incidences for different outbreak years. During 2022, a High-High cluster was observed in Kathmandu and its five neighboring districts, while Low-Low patterns were detected in ten western mountain districts (Figure). In 2023, two High-High clusters were detected, of which the first covers the districts of Kaski, Tanahu, Gorkha and surrounding districts, while the other one is in Dhankuta district. In 2024 single High -High cluster was observed in Kaski and 10 neighboring districts, while a Low-Low cluster was observed in mid-western mountain districts.



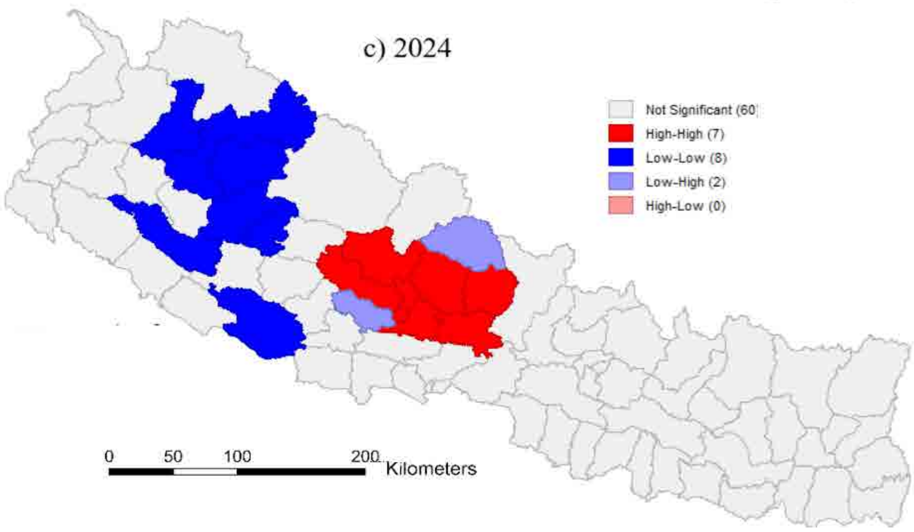


Figure 1: District level spatial clustering of dengue cases for outbreak years 2022, 2023 and 2024

The monthly analysis showed first six months (January to June) of a year in Nepal are normally dengue free and even if reported, the patterns are sporadic. For example, in 2022, only 165 cases were reported during the first 6 months which was 0.3 percent of the total annual cases. Similarly, in 2024 the total reported cases during the first 6 months were only 1.4 percent. However, it was slightly higher in 2023 which was 4.4 of the total annual cases. Regarding the spatial distribution, the 2022 dengue outbreak remained highly focal, with persistent High-High cluster developed in Kathmandu in August. These cluster remined relatively stable in shape and surrounding neighborhoods throughout the year. Similarly, The Low-Low clusters that developed in western Nepal showed minimal change over time. In contrast, 2023 exhibited greater spatial instability. Initially, cases began rising. In the beginning, when in July, a the High-High cluster developed in the Eastern Tarai. However, by the later months of the year, the cluster had shifted to the western mountain region.

In 2024 the western hill districts, especially Tanahu, Kaski and Parbat formed consistent High-High clusters in the early stages of the outbreak. From October onward, however, Kathmandu and its neighboring districts became High-High clusters. The Low-Low cluster of western mountain and hill districts persisted throughout the year, while other Low-Low clusters developed over and disappeared intermittently during the different months.

3.2 Spatial drivers of dengue for 2022-2024

Figure 2 presents the results of Random Forest Model, based on the 5 -fold cross validation repeated 100 times across different outbreak years. Among the models, the one based on the 2024 outbreak year performed the best, showing a higher median R squared and lower RMSE and MAE values. In contrast, the model for the 2022 outbreak year showed the poorest performance.

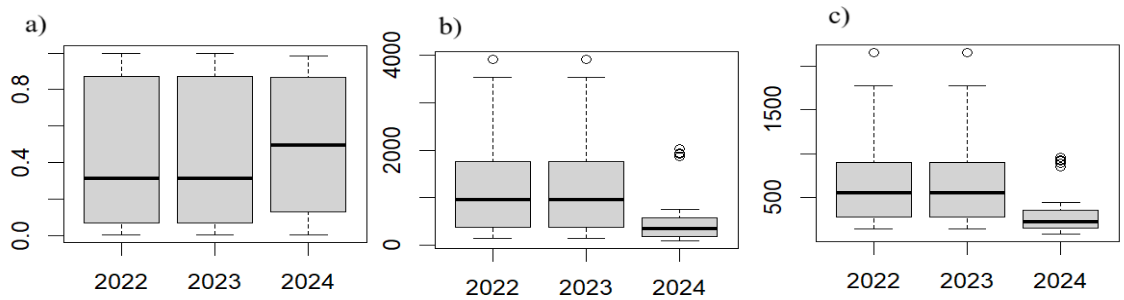


Figure 2: Summary Statistics of 5-fold cross validation of three different years random forest regression model a) R Squared b) RMSE and c) MAE

Random forest models fitted for each outbreak year were used to predict dengue cases and compared with observed and predicted values using the goodness of fit (R squared). The models for 2022, 2023, and 2024 demonstrated strong predictive performance with R^2 values of 0.89, 0.75, and 0.85, respectively (Figure 3). Additionally, spatial distribution patterns between the observed and predicted dengue cases were consistently aligned across all years.

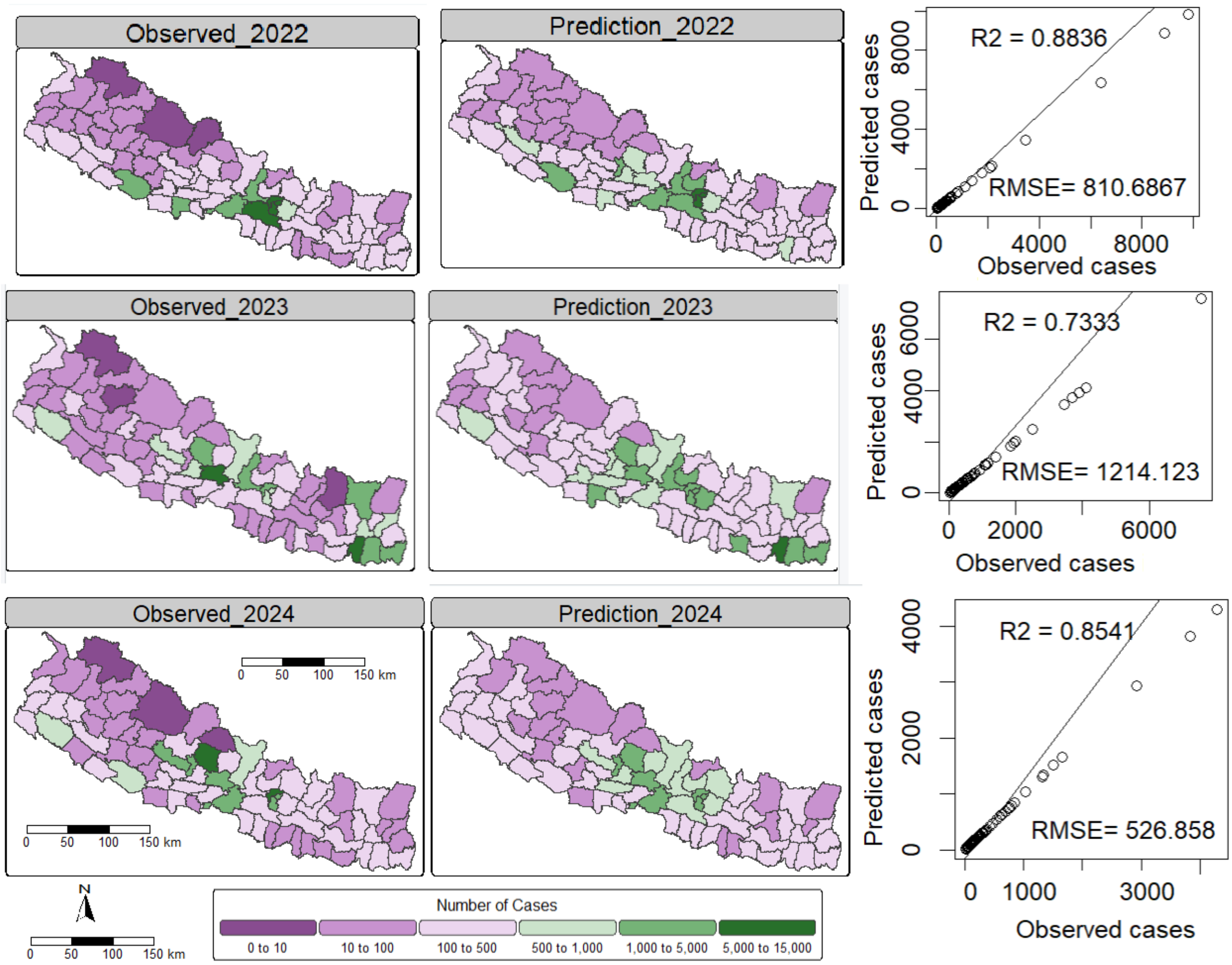


Figure 3: Observed vs predicted distribution of dengue cases during the 2022, 2023 and 2024 outbreak years

Each yearly model demonstrated occurrences of both underprediction and overprediction, indicating varying levels of accuracy across districts. Underprediction was particularly evident in districts with a high number of reported cases. Conversely, overprediction was more common in districts with low case numbers, where the models tended to estimate more cases than were observed.

The variable importance assessment identified Night-Time Lights (NTL), road density, precipitation, human footprint, and mean daytime Land Surface Temperature (dLST) as the five most influential spatial drivers of dengue in Nepal. NTL was ranked as the most important variable in 2022, third in 2023, and second in 2024. Road density consistently ranked as the second most important variable in both 2022 and 2023, and fourth in 2024. Human footprint was ranked first in 2023, third in 2024, and fourth in 2022. Precipitation emerged as the top predictor in 2024, while ranking third in 2022 and fourth in 2023. Mean dLST consistently ranked fifth across all three years of models.

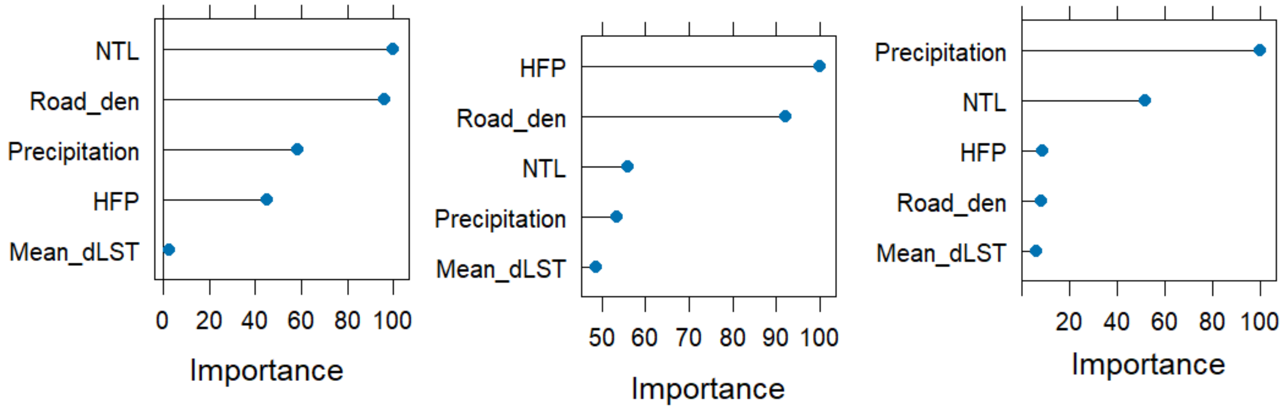


Figure 4: Variable Importance with top 5 predictor variables to explain spatial variation of dengue incidence during the outbreak year a)2022 b) 2023 and c) 2024 entire outbreak year.

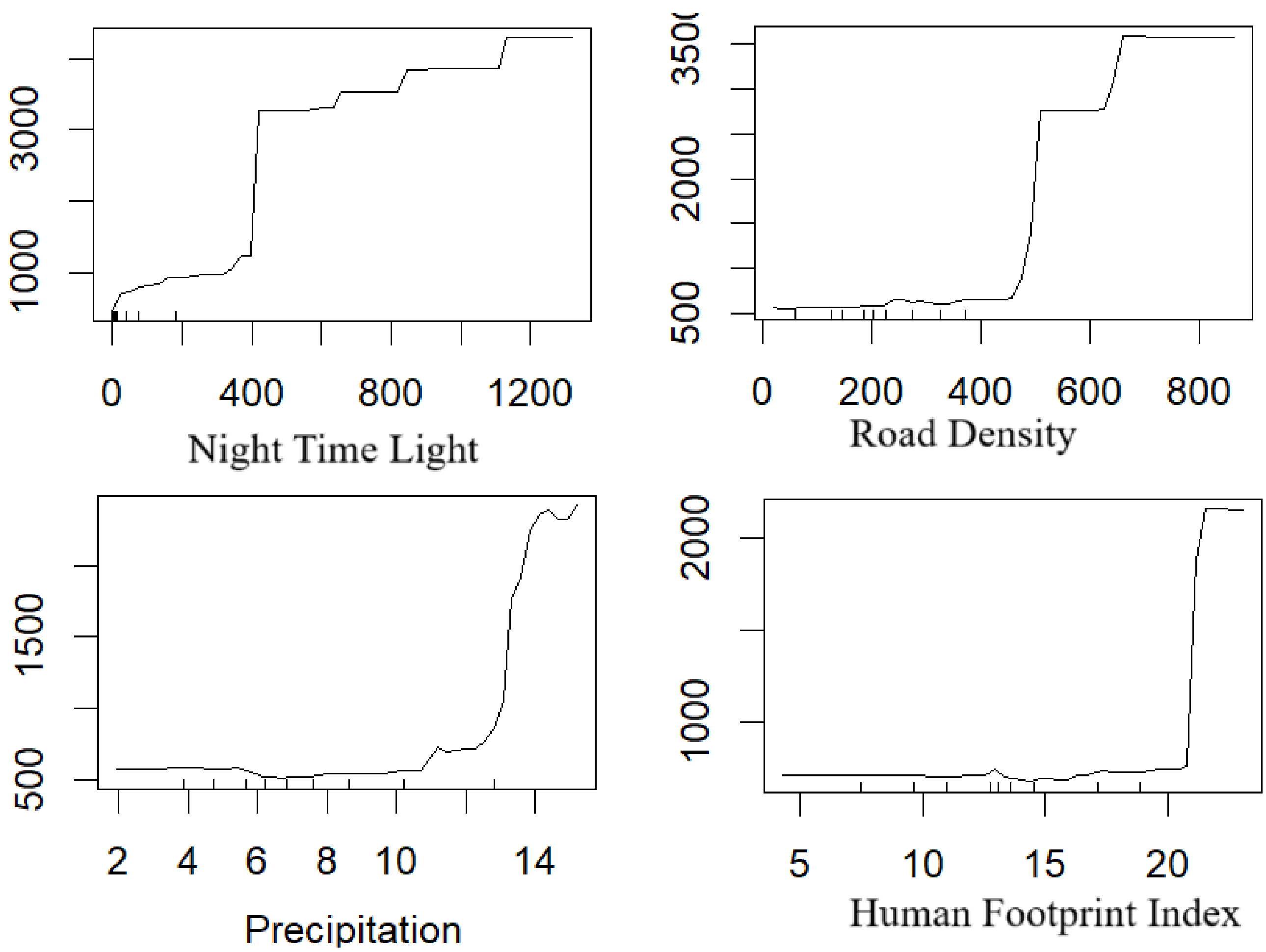


Figure 5: Response Curves represent the fitted partial dependence curve for 4 most influential variables of 2022 outbreak model

The partial dependency plot shows the positive nonlinear relationship with the four most important drivers in all three models. The positive relationship with rise of risk with different thresholds in different years. In 2022, the model when the threshold of road density exceeds 400, the risk of dengue transmission rise sharply, while this threshold was 300 for 2023 and 200 for the 2024 model.

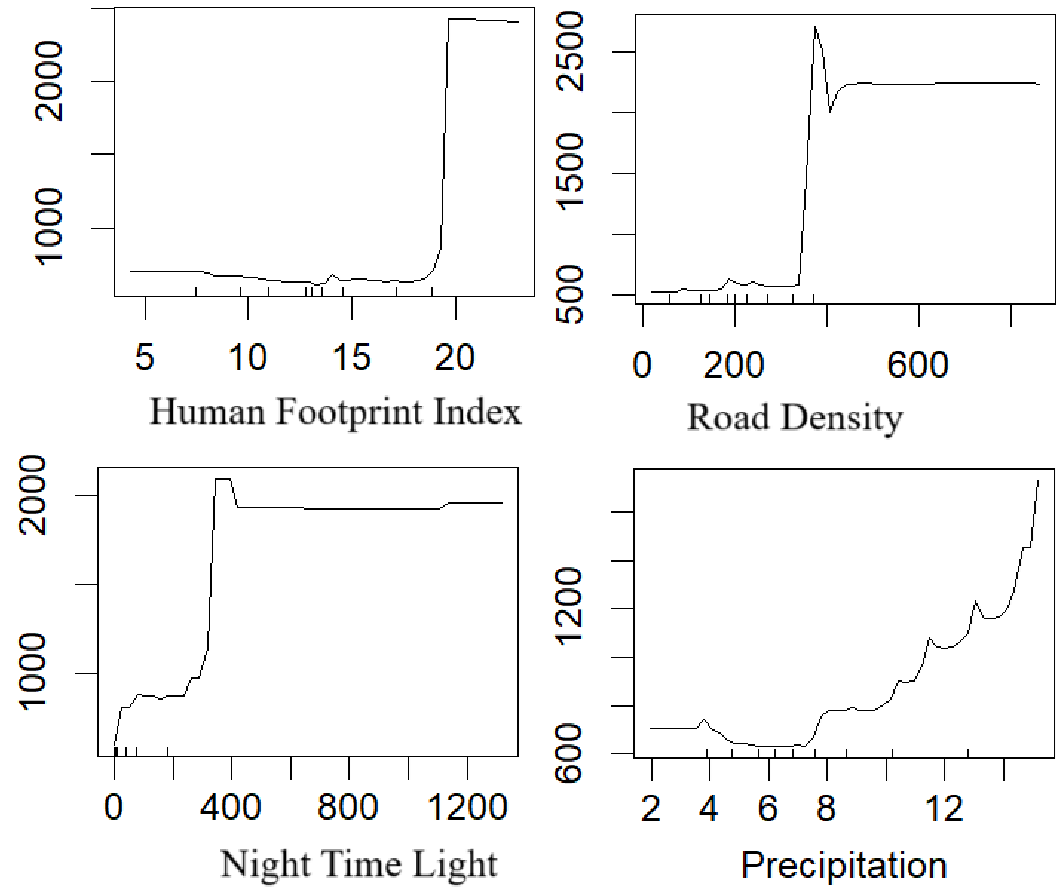


Figure 6: Response Curves represent the fitted partial dependence curve for 4 most influential variables of the 2023 month model

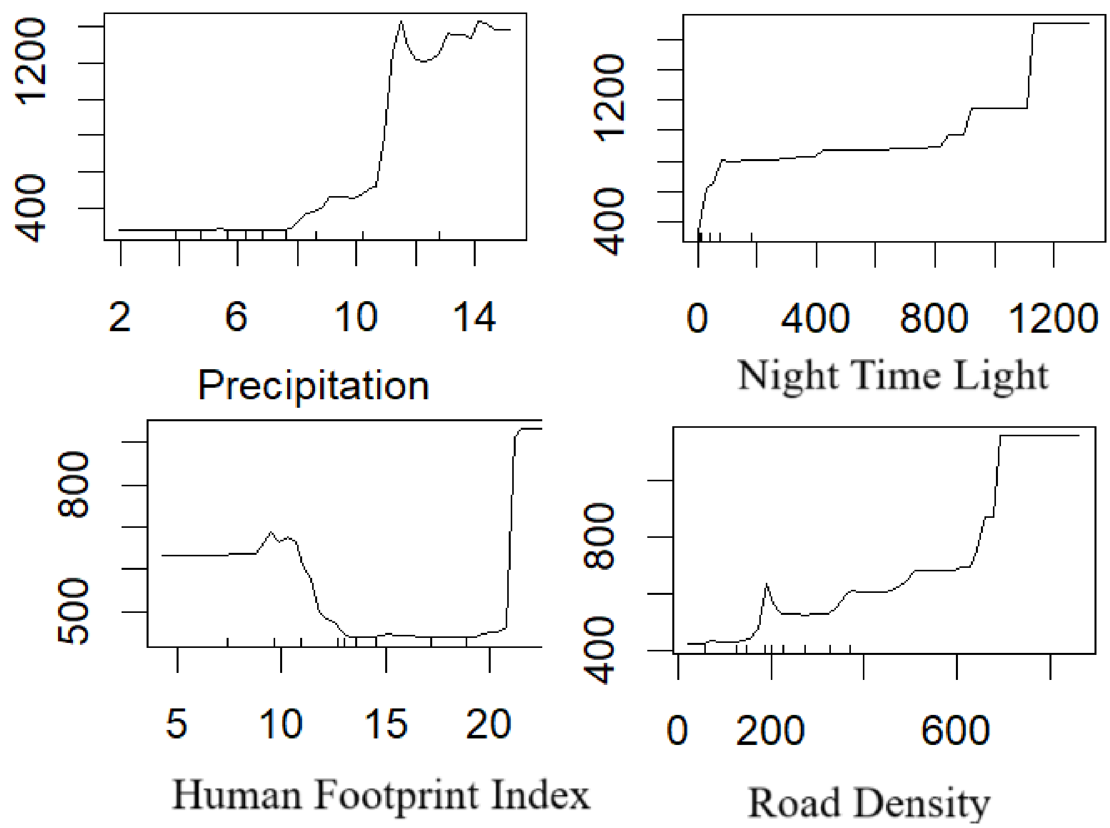


Figure 7: Response Curves represent the fitted partial dependence curve for 4 most influential variables for 2024 model

The response of NTL and road density was similar, with a sharp increase in dengue risk observed at critical values of 400, 500 and 600. . The influence of human footprint is similar in the 2022 and 2021 outbreak year model, where the risk of dengue rises sharply when the value reaches around 20. In both models, there is no change in risk until 20. However, in 2024 outbreak year model the risk first decreases from 10-15 and abruptly rises to 20. Regarding the effects of precipitation, it seems that when the precipitation reaches around 8, the risk rises sharply. The critical value for precipitation for 2022 was 10. Regarding precipitation, the 2022 model indicates a sharp rise in risk when precipitation reaches around 10. In the 2023 and 2024 models, this critical threshold is slightly lower, at approximately 8.

4. Discussion

In this study, we analyzed the spatiotemporal dynamics of dengue in Nepal over the past three years (2022- 2024). We utilized publicly available datasets along with environmental and socioeconomic drivers obtained from various open geoportals, we conducted a comprehensive analysis of dengue distribution across the country Our analysis revealed significant spatial variation and heterogeneity in the distribution of dengue between outbreak years. Spatial autocorrelation analyses indicated a non-random distribution, highlighting distinct dengue clusters detected in various regions of the country. These outbreaks during these years were primarily associated with urbanization levels and regional variability in rainfall, underscoring the role of both anthropogenic and climatic factors in shaping outbreak dynamics. Our analysis found marked spatial variations and heterogeneity in the spatial distribution patterns of dengue incidence throughout the study period. The level of heterogeneity, however, varied over the years. In 2022, the distribution was highly heterogenous and more clustered and exhibited greater spatial concentration, particularly in Kathmandu, compared to the other two years. In contrast, the dengue incidence in 2023 was more dispersed and exhibited lower heterogeneity. While 2022 remained highly focal, subsequent outbreak in 2023 and 2024 demonstrated westward shift in their primary hotspots.

A significant shift in the spatial distribution of dengue was observed in Nepal beginning in 2022. Before this, dengue was mainly reported from the lowland Tarai region and with only sporadic cases from mountain and hill districts, including Kathmandu where a first major outbreak had occurred in 2019, while foci of the disease remained in the lowlands[17,34]. However, since 2022 outbreak, Kathmandu and other hill districts has emerged as persistent foci of transmission. Monthly analysis showed these hotspots not only emerged but also sustained transmission for a long duration. Notably, Kathmandu remained a hot spot continuously throughout the entire 5-month outbreak duration in 2022 (Figure). The possible reason of the emergence and sustainability of dengue hotspots in the hilly district could be extended temporal windows of the thermal environment of mosquito vector survival and activity in Nepal[35] .These findings suggest that, despite being located in a higher altitude and cooler climate, Kathmandu and other highly populated areas of hill districts become vulnerable for future large-scale outbreaks. Being a center for international travel, Kathmandu further increases cross -border transmission and potential outbreak. Nevertheless, we did not find significant changes in temporal patterns compared to the previous year [36]. Similar to the previous year, sporadic dengue cases were reported from the first month of the year, but ascended sharply only from July-August, reaching the peak in September.

The accuracy of the random forest model also varies across the outbreak years. The median value of RMSE and MAE

Based on the model evaluation metrics, the 2024 outbreak model was best compared to the model of 2022 and 2023 outbreak models. The potential reason could be overfitting, poor transferability to new ("unknown") contexts. Such issues can be in different disease modelling[37]. Our results reveal district-level spatial variations in dengue incidence is largely explained by the selected environmental variables, with noticeable differences across outbreak years. We found a strong role of socioeconomic factors in explaining spatial variations in throughout all modeled years [38]. Together with socioeconomic factors the influence of precipitation was also found important to driver of spatial variation. Conversely, temperature showed relatively weak association with spatial heterogeneity of dengue incidence across the year. These results align with a previous study highlighting the greater influence of socioeconomic factors compared to climate and environmental factors. However, a multiple -year study, climate factors remain equally important [39]. For example, while the 2013 dengue outbreak of Guangzhou was largely explained by population density, NTL and land use studies spanning multiple years identified relative humidity, temperature and precipitation as key contributing factors.

Specifically, five variables, including road density, NTL, Human Footprint Index, and precipitation daytime LST remained important in explaining district -level spatial variation and heterogeneity of the 2022 outbreak. These variables have already been proven useful to explain the spatial process of dengue in different dengue endemic regions worldwide. For example, population density was positively associated with dengue transmission as observed in swat Pakistan in 2022 [40], several studies in China . The strong positive role of road density was observed in Guangzhou, and the West Indies [41–43]. The NTL was found to be positively associated in two different studies in China [39,44]. Building density was found to be positively associated with dengue in Thailand [45] while POI density played a notable role in Guangzhou, China [46]. Numerous studies have also confirmed a positive association can be seen with the proportion of urban areas and dengue transmission. Finally, as in Vietnam, human population potential (HPP) remained most informative to explain spatial variability and heterogeneity during the different years outbreak [47] ranking in the top in the 2023 model.

The top 4 most important variables identified in explaining the spatial distribution pattern of dengue outbreaks were closely related to urbanization. Urbanization favors a closer proximity between mosquito vectors and human populations, thereby facilitating the spread of mosquito-borne viruses[48]. Along with, high population density, unmanaged urban infrastructure, and relatively high human mobility in urban settings, accelerates the dengue transmission. [49]. High population density provides a susceptible population for the transmission, while poor urban infrastructure provides a micro aquatic habitat for the breeding and proliferation of the mosquito vector, thereby promoting dengue transmission[49]. The informal and slum or slum like settlement characterized by both high population density, poor urban infrastructure facilitates the transmission chain in the urban environment [50]. The recent findings also suggest that direct NTL can contribute directly in dengue risk by increasing biting behaviors of Aedes mosquitoes [51].

Given that dengue is highly focal disease, high resolution data is imperative to locate the spatial distribution of disease clusters more precisely and pinpoint the target areas for intervention. If this study had been conducted at more granular level at least at the municipal level, the evidence could have provided more useful and actionable insights for dengue control program. We therefore urge the health authority to make fine resolution disease data publicly available at municipal level, to enable the generation of more useful evidence for municipal dengue control program strategies. As municipality in Nepal being local level government authorities, analyses at the municipal level are especially useful to execute effective health polices in control and guiding interventions against dengue.

Partial dependence plots revealed positive nonlinear relationship between spatial distribution of dengue and selected variables for the different years. In line with our studies, several previous studies have observed a nonlinear association between dengue incidence and environmental drivers. However, the threshold levels at which these selected drivers began to increase dengue risk varied by year indicating environmental drivers influenced the spatial distribution of dengue differently over time in Nepal. For example, the threshold for road density above which the risk of dengue rose was highest in 2022, indicating a more urban-centered outbreak that year. In contrast, the lower threshold value observed in 2023 and 2024 indicates a more dispersed and widespread pattern of dengue distribution.

This study is important to enrich to the spatial epidemiology of infectious disease research in Nepal. Despite the growing public health problem, there is limited knowledge on the spatiotemporal dynamics and associated drivers in the distribution of dengue in Nepal. We focused on major outbreak years, which cover more than 80 percent of reported dengue cases in Nepal to date. Thirdly, we illustrated the importance of open data; both disease incidence and environmental drivers in advancing of spatial epidemiology. The importance of open data has also been highlighted in disease risk mapping in earlier research [52].

However, some inherent limitations must be acknowledged with this study. For example, being coarse resolution of the data, we were unable to pinpoint high risk areas within Kathmandu and the neighborhood. Since dengue is highly focal disease, high spatial resolution study is imperative to inform the related control intervention more precisely. Another limitation is underreporting caused by passive surveillance and inadequate health infrastructure which likely led to a substantial underestimation of outbreak magnitude. Therefore, the spatiotemporal quantification done here should not be taken actual situation but closer to reality and should be interpreted as approximations rather than exact representations. Similarly, while our analysis explores a global association between dengue and environmental variables, recent studies suggest these relationships can be spatially. Future studies should account for spatial heterogeneous relationships by implementing geographical weighted regression or a similar spatial explicit method, to better capture this heterogeneity.

5. Conclusion

This study assessed the spatiotemporal dynamics of dengue outbreaks in Nepal from 2022 to 2024 along their associated drivers, using geospatial analytics and machine learning techniques.

We observed significant spatial variations and heterogeneity in dengue incidence across Nepal and between the study years. Highest heterogeneity was observed in 2022 while 2023 is much homogeneous distribution. However, statistically significant dengue clusters were detected in each year. Notably, the hotspot is being shifted toward west from Kathmandu. The random forest model indicated that district-level variation in dengue incidence could be explained by selected environmental variables, although the model's predictive power varied across the years. Environmental predictors related to urban characteristics such as night-time lights (NTL), road density, Human footprint index and together with precipitation significantly explain rent years spatial variations and heterogeneity of dengue incidence in the. These findings can support the development of informed evidence-based control strategies and more targeted public health interventions

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