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Modelling the effect of climate change on prevalence of malaria in western Africa

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Malaria is a leading cause of infectious disease and death worldwide. As a common example of a vector-borne disease, malaria could be greatly affected by the influence of climate change. Climate impacts the transmission of malaria in several ways, affecting all stages of the disease's development. Using various weather-related factors that influence climate change, this study utilizes statistical analysis to determine the effect of climate change on reported malaria rates in an African region with endemic malaria. It examines the relationship between malaria prevalence and climate in western Africa using spatial regression modeling and tests for correlation. Our analysis suggests that minimal correlation exists between reported malaria rates and climate in western Africa. This analysis further contradicts the prevailing theory that climate and malaria prevalence are closely linked and negates the idea that climate change will increase malaria transmission in this region.

Keywords and Phrases: statistics, disease, spatial regression model.

1 Introduction

Malaria is one of the most devastating vector-borne parasitic diseases in the tropical and subtropical regions of the world. This burden plagues over 100 countries worldwide, and approximately 40% of the world lives in areas in which malaria is endemic,

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mostly in developing countries (Suh *et al.*, 2004; RBM/WHO/UNICEF, 2005). In these countries, malaria is the fourth leading cause of childhood deaths (following neonatal causes, acute lower respiratory infections, and diarrhea), directly resulting in 8% of deaths in individuals 5 years of age or younger. (WHO, 2005).

According to the WHO (2008), Africa carries the highest burden with more than 198 million cases reported in 2006. The Centers for Disease Control and Prevention estimate that between 700,000 and 2.7 million persons die annually from malaria (Suh *et al.*, 2004). The African region bears 90% of these estimated worldwide deaths (WHO, 2008) and three-quarters of all malaria related deaths are among African children (Breman, 2001).

Malaria is characterized primarily by its main symptom – a high fever – and is caused by one of four species of parasites of the genus *Plasmodium: falicparum, vivax, ovale*, and *malariae. Plasmodium falciparum* is the most deadly of the four strains, and the most common form found in sub-Saharan Africa. *Plasmodium vivax* is the primary malaria parasite on the densely populated Asian continent, but it is rarely fatal. *Plasmodium ovale* and *P. malariae* are less common and less severe, and thus receive less public attention. (RBM/WHO/UNICEF, 2005).

Female *Anopheles* mosquitoes serve as the vector infecting humans with the *Plasmodium* parasite. Out of about 60 anopheline mosquitoes able to transmit malaria to humans, there are three primary vector species, namely (i) *Anopheles funestus*, (ii) *Anopheles arabiensis*, and (iii) *Anopheles gambiae sensu stricto*. Anopheles funestus belongs to the *A. funestus* group, while *A. arabiensis* and *A. gambiae sensu stricto* belong to the *A. gambiae* complex (Coluzzi, 1984; Gillies and DeMellion, 1987; Hargreaves *et al.*, 2000). These are the most efficient vectors of the malaria parasite incriminated in the transmission of the most severe and deadly form of malaria in Africa. To date, the situation is exacerbated by the rapid development of drug-resistant malaria parasites as well as insecticide-resistant *Anopheles* vectors.

In malaria endemic countries, climate factors (particularly rainfall, temperature, and humidity) reportedly contribute to the increased number of mosquitoes and thus make transmission favorable. The Centers for Disease Control and Prevention (www.cdc.gov) states,

> Once adult mosquitoes have emerged, the ambient temperature, humidity, and rains will determine their chances of survival. To transmit malaria successfully, female Anopheles must survive long enough after they have become infected (through a blood meal on an infected human) to allow the parasites they now harbor to complete their growth cycle ('extrinsic' cycle) .... Warmer ambient temperatures shorten the duration of the extrinsic cycle, thus increasing the chances of transmission.

Based on this information, we chose common weather variables that indicate temperature, humidity, and precipitation for this study. Higher temperatures as well as higher rainfall and flooding are considered to play a role in increasing malaria transmission (see www.Scidev.net). Rainfall produces surface water that serves as breeding sites for malaria vectors. Temperature also affects the development of both the *Anopheles* vectors and *Plasmodium* parasites. The interaction between optimum rainfall and temperature regimes further increases atmospheric humidity, thus supporting mosquito survival. Prevailing climatic/environmental conditions affect their vectorial capacity (i.e. new infections produced by the vector per case per day), which determines how malaria is transmitted and expressed in individuals and populations (Gillies and DeMellion, 1987). It has been reported that global changes in temperature, rainfall, and humidity could lead to increased risk of vector-borne diseases including malaria (Martens *et al.*, 1995; Martin and Lefebvre, 1995; Patz and Lindsay, 1999; Kovats *et al.*, 2001; Patz *et al.*, 2002). In particular, it has been studied that the increase in climate change positively associates with an increase in mosquito rates (see Kearney *et al.*, 2009). Meanwhile, other studies positively associate mosquito rates and malaria (see Centers for Disease Control and Prevention, 2004). Thus, this study analyzes the transitive relationship between climate change and malaria rates.

Although malaria demands attention throughout the world, the disease is a pressing public health concern on the continent of Africa. There is no consensus, however, on the potential effect of climate change and/or variability on malaria prevalence in Africa. This is partly due to the underlying rationale behind different methods. For example, instead of models based on actual observed statistics, biological principles are the foundation of some assessments. Martens *et al.* (1995) utilized a biological approach to consider the impact of temperature and precipitation on *Anopheles* and *Plasmodium* reproduction rates. They conclude from their ecological systems analysis that, as climate trends in the direction forecasted by the Intergovernmental Panel on Climate Change, the transmission and epidemic potential of malaria will increase substantially by the year 2100 (Martens *et al.*, 1995).

Rogers and Randolph (2000) discuss the problem from a different perspective. Their study utilized statistical analysis to challenge many of the biological assumptions surrounding the potential connection between malaria prevalence and climate change. They based the analysis on the present-day distribution of *P. falciparum* and developed a multivariate climate constraint model more sensitive to how the relationship between climatic variables impacts transmission. This model was then applied to future global circulation models created by England's Hadley Centre. The study found 'remarkably few changes, even under the most extreme scenarios' and concluded that 'the quantitative model presented here contradicts prevailing forecasts of global malaria expansion' (Rogers and Randolph, 2000). Their study, however, considers only the spread of malaria to new areas, and does not attempt to quantify how climate change could impact malaria prevalence in currently endemic areas. Furthermore, most of the research in this area is focused mainly in areas of unstable transmission, such as desert fringe and highland areas (Lindsay and Martens, 1998; Kovats *et al.*, 2001; Hay *et al.*, 2002). There are few or no studies carried out in endemic areas and particularly in western Africa.

Research also offers conflicting explanations for the recent resurgence in epidemic malaria witnessed in eastern Africa, especially in the highland regions (Kleinschmidt *et al.*, 2000; HAY *et al.*, 2002; KAZEMBE *et al.*, 2006). This debate, however, has focused on whether the region's change in climate is statistically significant during the time period of increased malaria prevalence (KAZEMBE *et al.*, 2006). Although HAY *et al.* (2002) do not believe that past or current malaria surges in the region are the result of climate change, they do agree that climate change will influence areas susceptible to malaria transmission in the future (KLEINSCHMIDT *et al.*, 2000). Though these studies focus on areas of emerging epidemic malaria, they, do not consider potential impacts in malaria prevalence in endemic areas, such as western Africa.

Climate change and/or variability may work with or against efforts to bring malaria under control. There is renewed interest in malaria control particularly in Africa following the Abuja declaration, the launch of the Roll Back malaria (RBM) partnership between the public and private sector, United Nations Millennium development goals and scaling up of interventions through Global Fund (BRUGHA and WALT, 2001; GREENWOOD and MUTABINGWA, 2002; TEKLEHAIMANOT and SNOW, 2002). Identifying changes in malaria risk due to changes in existing climatic conditions is therefore important for monitoring the impact of new interventions particularly in endemic areas.

Because we are not able to incorporate mosquito information directly in our statistical analysis, our study instead analyzes the transitive relationship between weather variables and malaria rates. This analysis uses descriptive statistics and spatial regression techniques to examine the link between malaria rates and climate in western Africa. The goal is to develop predictive models that describe the association between weather variability and malaria risk in western Africa. Understanding this association can then inform how altered weather resulting from climate change may influence malaria rates in the region.

2 Methods

2.1 Data

Focusing on ten countries in western Africa, we linked reported malaria cases and deaths from the years 1996 to 2006 obtained from the *World Malaria Report* (2008) with climate data from the National Oceanic and Atmospheric Administration's National Climatic Data Center (NCDC; http://www7.ncdc.noaa.gov). The ten countries included in this study are Benin, Burkina Faso, Cote d'Ivoire, Gambia, Ghana, Liberia, Mali, Senegal, Sierra Leone, and Togo (Figure 1).

The weather information is obtained from the Surface Data Monthly information made available by the NCDC (http://www.ncdc.noaa.gov/cgi-bin/res40.pl#F). The data included are monthly, locally reported weather station observations of 18 indicators (averaged to obtain yearly values); where necessary, the associated units are provided in parentheses for each explanatory variable. In particular, we include mean station pressure (mb), mean sea-level pressure (mb), mean temperature (°C), departure of

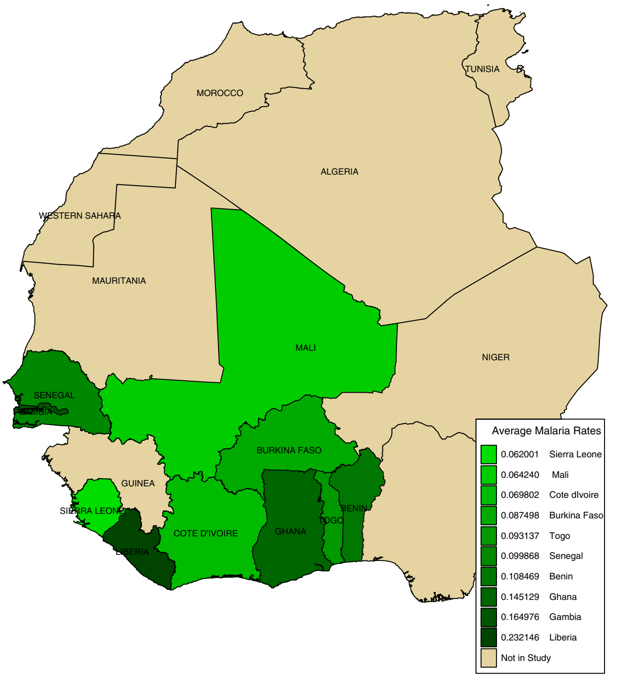

Fig. 1. Map of western Africa and average malaria rates (averaged across time) for ten countries in western Africa from 1996 to 2006. The associated grayscale (light to dark) corresponds to the range of average malaria rates (low to high).

temperature from average (°C), mean vapor pressure (mb), number of days with precipitation at least 1 mm, total precipitation (mm), and departure of precipitation from average (mm). Mean vapor pressure is the part of the atmospheric pressure due to the water vapor content and is used to reflect the amount of humidity present in the atmosphere. Mean temperature and departure of temperature from average serve to incorporate how temperature changes associate with malaria rates. Analogously, the precipitation variables incorporate the amount of rainfall into the analysis.

The number of reported malaria cases and deaths were obtained from the *World Malaria Report* 2008 (WHO), along with the population of each of the ten countries included in this study. Malaria rates were computed as malaria cases divided by the associated population size in each country.

2.2 Statistical analysis

Spatial regression analysis and tests for correlation were used to examine the relationship between malaria rates and local weather indicators for the ten countries in western Africa. The dependent/outcome variable was the malaria rate for each country. Table 1 shows the mean, median, minimum, and maximum values for all

Table 1. Descriptive statistics for all weather-related variables, as well as population size, number of malaria cases, and associated malaria rates in the ten western African countries

Variable	Minimum	Median	Mean	Maximum
Number of malaria cases reported	7192	713,319	942,503	3,552,896
Deaths	36	1226	1565	8083
Mean station pressure (mb)	943.8	1000.4	993.6	1011.7
Mean sea level pressure (mb)	901.5	1010.6	1009.3	1013.0
Mean temperature (°C)	24.88	27.36	27.36	29.17
Departure of temperature from average (°C)	−1.35	0.1690	0.5861	2.80
Mean vapor pressure (mb)	17.39	27.40	25.40	31.10
Number of days with precipitation $\geq$ 1 mm	0.670	5.460	5.225	13.160
Total precipitation (mm)	11.00	81.88	262.48	3344.33
Departure of precipitation from average (mm)	−87.00	−6.345	−10.813	107.600
Population size	1,192,548	8,598,592	9,201,897	22,478,658
Malaria rate	0.001	0.099	0.112	0.375

The summary information includes the associated minimum, median, mean, and maximum values for each variable.

Table 2. Mean number of reported malaria cases (between 1996 and 2006) for each of the ten western African countries.

Country	Mean number of reported malaria cases
Benin	745,340.1
Burkina Faso	1,098,680.8
Cote d'Ivoire	1,203,705.8
The Gambia	229,505.9
Ghana	2,956,957.3
Liberia	613,171.1
Mali	691,245.7
Senegal	1,111,249.4
Sierra Leone	321,340.5
Togo	453,837.1

explanatory variables considered across all 10 countries during the time period of interest. Table 2 provides the mean number of reported malaria cases for each country during the associated time period.

Geographic data of this type often display a spatial autocorrelation (e.g. a country's values are similar to that of neighboring countries). Therefore, we tested for spatial clustering in our data set using Tango's Index (Tango, 1995), [Correction added after publication 18 May 2010; in the preceding sentence in the citation for Tango's Index, (Griffith, 1996) was corrected to (Tango, 1995).] which is defined as

$$T = \sum_i \sum_j w_{ij} \left(y_i - n_i \frac{y_+}{n_+} \right) \left(y_j - n_j \frac{y_+}{n_+} \right),$$

where i and j denote geographic units (e.g. counties), y_i is the number of cases at geographic unit i, n_i is the population at risk at geographic unit $i, n_+ = \sum_i n_i, y_+ = \sum_i y_i, N$ is the total number of geographic units, and w_{ij} is a weight assigned to the pair of geographic units i and j. A simple weight function based on adjacent neighbors is defined as

$$w_{ij} = \begin{pmatrix} 1 & \text{if } i, j \text{ are adjacent neighbors,} \\ 0 & \text{otherwise,} \end{pmatrix} \tag{1}$$

and used to model the spatial dependence. Tango's Index provides a summary over the entire study area of the level of spatial similarity observed among neighboring values. Large values of Tango's Index indicate spatial clustering.

We fit a simultaneous autoregressive model that uses a regression on the values from all locations to account for the spatial dependence to estimate variables that were predictors for malaria rates in each county. The statistical software package R (R Foundation for Statistical Computing, Vienna, Austria) was used for all analyses.

2.3 Notes

This study is limited to analyzing the connection between climate and malaria in the western Africa region, as defined by the United Nations (http://www.uneca.org). As data were not available for all 15 countries in western Africa, we use the ten countries with the most complete information. The study also considers only the years 1996–2006, due to the constraints of the *World Malaria Report* and NCDC data. Data from both sources before 1996 are not complete due to restrictions on data access, communication problems, or quality control measures protecting the integrity of the reported information. Climate data were not available for all locations during all years. Any missing values were imputed by averaging over available years. Outliers were detected in the data set via the $1.5 \times$ IQR criterion (Moore *et al.*, 2009). Accordingly, we found two outliers in the departure of temperature from average (both in Burkina Faso), three outliers in the departure of precipitation (Togo, Cote D'Ivoire, and Sierra Leone), two outliers in the mean sea-level pressure (Burkina Faso, and Sierra Leone), and three outliers in the reported malaria deaths (Mali, Liberia, and Cote D'Ivoire). We then performed a sensitivity analysis, analyzing the data with and without the outliers. This approach produced results that lacked any significant differences, thus we kept all data (including the outliers) in the model for our analysis. It was determined that the outliers were due to the small ranges of some of the variables.

3 Results

The study examined the relationship between reported malaria cases and rates with eight weather indicators. Descriptive statistics on all variables are summarized in Table 1. Table 2 presents the mean number of reported malaria cases in each country of interest. Ghana has the highest mean number of reported malaria cases (2,956,957.3) and Gambia the lowest (229,505.9). Figure 1 presents the malaria rates for all countries, showing Ghana, Gambia, and Liberia with the highest rates.

3.1 Correlations

Table 3 presents the Pearson correlation coefficients for all pairs of variables considered in the analysis. The strong correlation between some weather variables such

Table 3. Pearson correlation coefficients of considered variables (below diagonal) with associated P-values (above diagonal).

	Reported cases	Mean station pressure	Mean sea level pressure	Mean temperature	Departure of temperature from average	Mean vapor pressure	Number of days with precipitation ≥ 1 mm	Total precipitation	Departure of precipitation from average	Rate
Reported cases		0.011	0.131	0.361	<0.001	0.006	0.296	0.020	<0.001	0.026
Mean station pressure	*0.242		0.971	0.164	<0.001	<0.001	0.057	0.372	0.025	0.833
Mean sea level pressure	0.145	−0.003		0.464	0.006	0.117	0.963	0.756	0.048	0.006
Mean temperature	−0.088	−0.134	−0.071		0.199	0.059	<0.001	<0.001	0.836	<0.001
Departure of temperature from average	**−0.381	**0.485	−0.258	0.123		0.635	0.596	0.001	<0.001	0.501
Mean vapor pressure	**0.263	**0.596	0.150	−0.181	−0.046		0.682	0.013	0.137	0.126
Number of days with precipitation ≥ 1 mm	0.101	0.182	0.003	**0.373	−0.051	0.039		0.292	0.002	<0.001
Total precipitation	*−0.222	0.086	0.030	**0.491	**0.304	*0.237	−0.101		<0.001	0.008
Departure of precipitation from average	**0.371	*−0.214	*0.189	−0.020	**−0.615	−0.143	**0.289	**−0.328		0.055
Rate	*0.212	0.020	**−0.260	**−0.521	0.065	0.147	**−0.460	**−0.253	−0.184	

Coefficients that are statistically significantly different from zero at the 0.05 (0.01) level are denoted with *(**), respectively.

as mean station pressure and mean vapor pressure (0.596) was expected as station pressure is the atmospheric pressure with respect to the station elevation, and vapor pressure is the part of the atmosphere pressure due to the water vapor content (see http://www.noaa.gov). The positive correlation between these two variables implies that, as the vapor pressure increases, there is also increased pressure due to the water content in the atmosphere. Other expected strong weather correlations were detected, including departure of temperature from average and the departure of precipitation from average (−0.615). Both variables are important factors in climate and are the most widely measured variables. Changes in either variable can be associated with weather conditions that effect human health (either positively or negatively). For example, the strongest correlation with reported malaria cases was seen with the departure of temperature from average (−0.381). It is known that changes in temperature can effect changes in plant and animal species. In our study, we see that reported malaria cases are decreasing with temperature changes. In addition, the small correlation values for the number of reported cases and several other weather variables begin to cast doubt on the initial hypothesis that malaria prevalence is associated with climate change.

3.2 Spatial regression

Tango's Index was used to examine the spatial relationship between neighboring regions. Large values of Tango's Index indicate clustering. Using the adjacent neighbor matrix as defined in Equation 1, we obtained a value of 482,960 for Tango's Index (P-value <0.001), which indicates strong spatial clustering of the malaria rates.

Spatial regression modeling further analyzes the relationship between the weather variables and malaria prevalence. A simultaneous autoregressive model was used with all variables presented in Table 4 (with the exception of reported cases, and deaths) with malaria rates as the response variable. Several of the weather variables have negative coefficients (e.g. the estimated coefficients for mean sea-level pressure, departure of temperature from average, number of days with precipitation at least 1 mm, and total precipitation are -1.22×10^{-2}, -4.47×10^{-2}, -4.18×10^{-2}, and -4.63×10^{-5}, respectively) indicating that increases in each of these explanatory variables associates with a decrease in the rate of malaria exposure.

Mean vapor pressure, mean temperature, mean station pressure, and departure of temperature from average all have positive estimated coefficients, and thus imply a positive correlation between each respective explanatory variable and malaria rate. Although the above-mentioned variables increase the rate of malaria in these countries as some researchers have predicted with climate change, we found that other weather indicators of climate change [including number of days with precipitation at least 1 mm (estimated coefficient value equals -4.180×10^{-2}), departure of temperature from average (-4.477×10^{-2}), mean sea-level pressure (-1.224×10^{-2}), and total precipitation (-4.628×10^{-5})] actually decrease malaria rates. This indicates that

Table 4. Full spatial regression model with malaria rates as the response variable

Variable	Estimate	Standard Error
Intercept	9.087	9.884×10^{-5}
Mean station pressure	2.340×10^{-3}	4.259×10^{-9}
Mean sea-level pressure	-1.224×10^{-2}	9.713×10^{-8}
Mean temperature	4.553×10^{-2}	1.525×10^{-7}
Departure of temperature from average	-4.477×10^{-2}	7.011×10^{-8}
Mean vapor pressure	2.797×10^{-3}	2.427×10^{-8}
Number of days with precipitation $\geq$1 mm	-4.180×10^{-2}	7.161×10^{-8}
Total precipitation	-4.628×10^{-5}	6.674×10^{-10}
Departure of precipitation from average	1.962×10^{-4}	2.332×10^{-8}

All model coefficients are statistically significantly different from zero at the 1% significance level.

more research is needed in this field to determine the impact of climate change on malaria rates in western Africa.

4 Discussion

This work analyzed the relationship between a selection of weather indicators and malaria rates in ten countries in western Africa. Based on the given data, the analysis shows very little correlation exists between rates of malaria prevalence and climate indicators in western Africa. This analysis contradicts the prevailing theory that climate and malaria prevalence are closely linked and also negates the idea that climate change will increase malaria transmission in the region. Kazembe *et al.*'s (2006) study of malaria risk in Malawi included the mean maximum temperature in its final predictive model. This analysis, however, found little evidence for a significant relationship between temperature and malaria prevalence.

This analysis focused on western Africa, an area with endemic malaria where the climate is already favorable to malaria transmission. In such areas, changes in weather patterns may play less of a role in malaria transmission than they would in regions with seasonal, epidemic, or sporadic malaria cases. Weather variability caused by climate change may thus affect malaria transmission more in other regions than in the one considered here.

Climate is composed of a plethora of weather variables over a long period of time. The weather indicators selected here do not provide a complete picture of the region's climate. Our weather indicators were chosen based on an understanding of malaria transmission and earlier work reporting the potential link between climate change and malaria prevalence, as described previously in this study.

The possible existence of threshold weather observations required to significantly influence malaria transmission rates is another potential explanation for the lack of correlation in the data. As mentioned, research indicates that increased ambient temperature results in a shorter extrinsic incubation period for the *Plasmodium* parasites, and could thus lead to increased malaria transmission. The mechanism for the altered extrinsic incubation period is not fully understood, though. Perhaps the relationship between incubation period and temperature is not linear, but requires certain temperatures to be reached or even maintained to see a noticeable alteration. If the observed data did not include those critical threshold temperatures, no correlation would be seen between prevalence and temperature, even though such a relationship exists. More research should thus be conducted on the proposed mechanisms for climate to influence malaria transmission so that the possible constraints of the relationship between weather and prevalence can be better understood and considered in future analysis.

5 Conclusion

This work offers considerable impact to the effect of climate change on malaria rates, yet limitations still remain regarding this study. It would be interesting to perform a more refined regression analysis (e.g. at a regional level or across shorter time intervals) in order to obtain a more in-depth understanding of the relationship between these factors; however, this information is not currently available at the *World Malaria Report* (2008).

Additional studies examining the relationship between malaria and climate would also help elucidate the meaning and scope of this report. One important step in expanding this research is considering the potential influence of weather indicators for the seasons preceding a malaria survey. For example, if the previous dry season is especially dry, that would influence the size of the mosquito population at the time of the survey, thereby possibly influencing malaria transmission rates. Kleinschmidt *et al.* (2000) analyze malaria prevalence in Mali and show some evidence supporting this idea, including the mean maximum daily temperature for the previous March through May period in its final model.

Expanding the location of analysis to study a region with more inter-annual weather variation, such as a country impacted by El Nino cycles, to analyze a wider climatic range is another area for future work. A broader range of weather observations might include critical values that more directly affect *Anopheles* mosquitoes or *Plasmodium* parasites, and could thus show a more significant relationship between the weather variables and malaria transmission rates. Focusing alternatively on a smaller region with more accurate malaria information available (such as the area directly surrounding a hospital or clinic) might also yield different results.

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