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Spatiotemporal Relationship between Variability in Selected Climate Parameters and Malaria Transmission Trends in Different Altitudes of Lower Lake Victoria Basin

[1*] **Doctor Samwel Odhiambo Olela**
PhD Student: School of Law, Arts and Social sciences
Kenyatta University, Nairobi, Kenya

[2] **Professor George L. Makokha**
Senior Lecturer, School of Law, Arts and Social Sciences
Kenyatta University, Kenya

[3] **Doctor Kennedy Obiero**
Lecturer, School of Law, Arts and Social Sciences
Kenyatta University, Kenya

Abstract

Abstract: Consequences of Global Climate Variability and Change are among the biggest environmental threats and challenges the world is facing. Malaria burden is greatest in developing countries of the tropics especially Africa south of the Sahara. In Kenya, it is blamed on high rainfall, temperature and relative humidity. This study investigated spatiotemporal relationship between variability in selected climate parameters and malaria transmission in different altitudes of lower Lake Victoria Basin, Kenya.

The study used secondary data archived at sampled meteorological stations and health facilities. Flooded sampling of malaria morbidity cases from health facilities within selected sub - counties in three sampled counties was obtained from Kenya Health Information System (KHIS) for ten years (2011 - 2020). Meteorological data was obtained for twenty years (2001 - 2020) except for Kisumu Relative Humidity which was only available for 12 years (2009 - 2020). Pearson's moment correlation coefficient and regression were used to establish the strength of the relationship between malaria transmission, climate elements and altitude.

Given temperature ranging between 22.52^{0}C – 23.77^{0}C, RH of 58.77% - 67.74% and a mean annual rainfall of 1844.57, the study area was found to be well within climatic threshold for endemic malaria transmission. When correlated and regressed, none of the climate parameters revealed significant relationship with malaria transmission except monthly temperature and monthly malaria transmission in Migori County. Transmission significantly decreased with increase in altitude. All climate variables were eliminated leaving only altitude as the significant spatial determinant of malaria transmission. Climate therefore remained an insignificant spatiotemporal determinant of variability in malaria transmission in the study area.

Spatiotemporal Variability of Malaria transmission was significantly defined by altitude and proximity to the lake. This made the study zone LLVB, Kenya into three based on altitude and malaria transmission rates as follows: 1001m to 1200m – high transmission zones; 1201 to 1400 - medium transmission zones; 1401 to 1600 – low transmission zones. Meteorologists and the Medics should combine efforts to put remedial measures in place depending on altitude and time of the year. There is need to find out why some parts should experience upsurge while others like Migori County are experiencing reduction. These recommendations were necessary in the LLVB, Kenya for the realization of Kenya's vision 2030.

Key words

Selected climate parameters, malaria transmission trends, Lower Lake Victoria Basin, Climate variability, Different altitudes

I. INTRODUCTION

Among the biggest environmental threats and challenges the world is currently facing are consequences of Global Climate Variability and Change. Heightened temperatures which according to [13] are proposed to increase by 3^0C by the year 2100, increased rainfall and increased frequencies of other extreme weather events are some of the impacts. These impacts vary or are determined by where a person lives and how sensitive the people are [26]. Half of the world's population including 3.4 billion people in 92 countries is at risk. 1.1 billion being at higher risk. [13] identified Africa as the most vulnerable due to her high dependence on natural environmental resources.

Though previously wide spread, malaria transmission – mainly determined by temperature, rainfall and RH is dominantly confined to Africa where 91% of the malaria related deaths occur, 60% of the deaths being children under five years [7]. Of the 228 million cases in the world, 93% were found in the WHO African region [25]. According to [8] the most vulnerable are those in the third world countries.

Occurrences of climate extremes have increased in East Africa. The worst case regional scenario of climate change predicted an additional 75.9 million people at risk from endemic (10 – 12 months) exposure to malaria transmission in Eastern and Southern Africa by 2080 with the greatest population at risk being in Eastern Africa [24].

Malaria in Kenya accounts for 18% of out – patient consultations and 10% of hospital admissions [22]. 29% (14.4 million) of the Kenya's population live in malaria endemic areas with 19.7% (9.8 million) living in the eight counties of the Lower Lake Victoria Basin (LLVB) [3]. It is a threat with a prevalence rate of 27%, while in the rest of the country; the rates vary between 4% and 8% [7].

[22] identified the Lower Lake Victoria Basin (LLVB), Kenya, which includes eight counties with a total population of more than 8.7 million to bear the highest brunt of malaria in the country. From his 2016 report, these counties combined had 38/1000 cases as compared to 6/1000 elsewhere. They showed 26.7% parasitemia compared to 8.2% elsewhere. However, malaria is preventable and is curable [28].

During the study period (2011 – 2020), the relationship between variability in climate parameters (temperature, relative humidity and rainfall) and malaria transmission (morbidity) in the LLVB, Kenya were established using Pearson's Product Moment correlation coefficient and regression analyses.

II. METHODOLOGY

2.1 Study Area

The study was carried out in the Lower Lake Victoria Basin (LLVB), Kenya which covers eight counties: Migori; Homabay; Kisumu; Vihiga; Siaya; Kakamega; Bungoma; Busia. Three (Migori, Kisumu and Kakamega) were sampled for the study (Figure 1). LLVB counties are located between latitudes 1.15^0N and 1.75^0S, and longitudes 33.95^0E and 35.05^0E. The Basin covers an area of about 42,724km^2 making about 22% of the entire LVB. The shore line is 550Km, about 16% of the entire shore line and a lake surface of 4, 128Km^2, making 6% of the entire surface [16]. The land covering this area slopes from an altitude of 1550m in Migori County down to 1100m at its lowest in Siaya County, and then rises again to 1535m in Kakamega and 1559m in Vihiga Counties [19]; [10].

The climate of the LLVB is Equatorial modified by the presence of the Lake and surrounding Highlands. Rainfall ranges from 1100mm in Homabay County to 1971mm in Kakamega County, an average of 1556.5mm annually [4]. Temperature varies from 20.0^0C in Vihiga County to 22.5^0C in Homabay County. This was an average of 21^oC [4], [21]. There are two rainfall regimes with no real dry season (Figure 1). Vegetation cover includes swampy grasslands and swampy forests, dry grasslands and dry woodlands, savannah forests and tropical forests depending on altitude. Much of the vegetation has since been cleared to give way for other activities like agriculture, settlement, urbanization, various construction works like roads, industries among others [16]. Major economic activities are fishing, tourism, mining, service industry, power generation, agriculture with crops grown being maize, sugarcane, rice, beans, potatoes, vegetables among others [16].

County health facilities are Migori, Homabay, Kisumu, Kakamega, Busia, Mbale, Bungoma and Siaya. All are level 4 hospitals. The LLVB meteorological stations are Kisumu International Airport, Kibos Cotton Station, Busia Cotton Station, Ahero Irigation Scheme, Koru Coffee Research Station, Mumias Sugar Company and SONYSUGAR. The inhabitants include Suba-Luos, Luos, Kurians, Nandis, Luhyas, Somalis, and small pockets of Indians, Arabs and Nubians [6].

The LLVB, Kenya was preferred for this study because from the literature review, most of the studies carried out in this area hardly recognized the influence of existing altitude variations on climate variability, vector distribution, and hence malaria transmission. This study therefore sought to compare climate variability and malaria transmission trends in different altitudes of lower Lake Victoria Basin, Kenya.

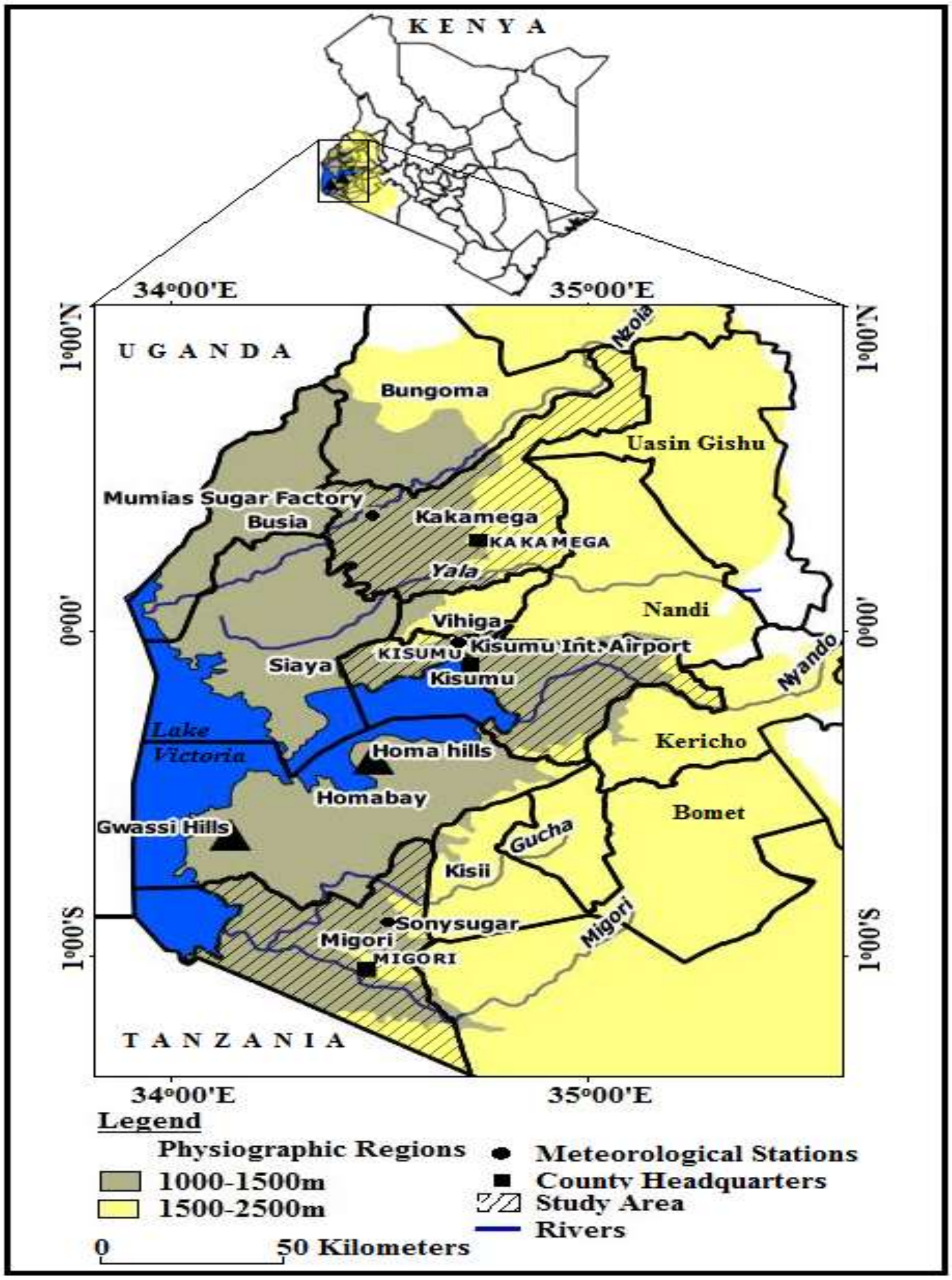

Figure 1: Map of the study area

Source: Modified from [9].

2.2 Data Collection and Data Characteristics

Monthly secondary data were obtained from routine malaria case transmission records archived by the Kenya Health Information System (KHIS), and climate data from selected Meteorological Centres. Malaria case transmission records for Kakameg County, Mumias West Sub-County (Level 4 Hospital), Kisumu County, Seme Sub-County (Level 4 Hospital) and Migori County, Awendo Sub-County (Level 4 Hospital) were all obtained from the Kenya Health Information System (KHIS) through Sub-County Hospital records offices. The health records were available for ten years (2011 - 2020) and were not categorized according to gender. The records included suspected (clinical) and confirmed (laboratory tested) cases for the < 5 years in age, the > 5 years in age, and malaria in pregnancy. Meteorological records on the other hand were obtained from South Nyanza (SONY) Central Meteorological Station (Code 9034145) for Migori County, Kisumu Airport Meteorological Station (Code 637080-9999) for Kisumu County and Mumias Sugar Company (MSC) Meteorological Station (Code 8934-133) for Kakamega County. Daily records for three selected climate parameters: temperature in degrees centigrade, percentage relative humidity and rainfall in millimeters were collected for twenty years (2001 - 2020) except Kisumu Airport Relative Humidity which was only available for twelve years (2009-2020) at the time of collection.

2.3 Data Analysis

All data collected were harmonized before being used. The study used Shapiro Wilk W test for normality to examine how the sampled data fitted to normal distribution at P value ≥ 0.05. Tukeys Honest Significance Difference (HSD) test was used to determine the strength of the significance of relationships. Time series analysis was used to determine the trends. Pearson's Product Moment Correlation Coefficient and ARIMA Regression models were the major anlytical tools used.

III. RESULTS

3.1 Spatiotemporal Relationship between Variability in Climate Parameters and Malaria Transmission in Different Altitudes of the LLVB

During the study period (2011 – 2020), the relationship between variability in climate parameters (temperature, relative humidity and rainfall) and malaria transmission (morbidity) were established using Pearson's Product Moment correlation coefficient and regression analyses. Following were the observations made:

3.1.1 Relationship between Monthly Climatic Elements and Malaria Transmission

3.1.1.1 Kakamega County

In Kakamega County, Mumias West -Sub County, temperature (r = 0.0071), RH (r = 0.4003) and rainfall (r = 0.4511) all correlated positively with malaria transmission. Of those relationships, none was significant (Table 3.1) implying that none of the parameters could confidently be used to explain the behavior of malaria transmission in Kakamega County. However, unlike [17] established in West Africa that transmission mostly depended on temperature and rainfall, in Kakamega County, the three climate parameters were always optimal and positively influenced transmission. This was an indication that although the relationship was not significant, malaria transmission cyclically patterned up with climate trends.

Table 3.1: Correlation analysis for Relationship between Mean Monthly Malaria and climatic parameters in Kakamega

```
. pwcorr Malaria Temp  Rainfall RH, obs sig
```

	Malaria	Temp	Rainfall	RH
Malaria	1.0000			
	12			
Temp	0.0071	1.0000		
	0.9825			
	12	12		
Rainfall	0.4511	-0.1244	1.0000	
	0.1410	0.7001		
	12	12	12	
RH	0.4003	-0.7208	0.7188	1.0000
	0.1973	0.0082	0.0084	
	12	12	12	12

The relationship between temperature and malaria transmission and between RH and malaria transmission in Kakamega County were confirmed to be positive following regression models of, $Y = -50050.63 + 1761.63X_2$ Where Y = Cases of confirmed malaria, X_2= temperature, and $Y = -50050.63 + 226.7999X_3$ Where Y = Cases of confirmed malaria, X_3= RH. Rainfall on the other hand regressed negatively with $Y = -50050.63 - 5.26488X_1$ Where Y = Cases of confirmed malaria, X_1= rainfall. None of the relationships was significant, adding to the regression R^2 value of the line of best fit at 38.09%, none of the parameters could confidently be used to explain the behavior of malaria transmission in Kakamega County. However, at this stage, transmission was attributed to temperature and RH because they maintained a positive relationship through the correlation and regression (Table 3.2).

Table 3.2: Regression analysis for monthly malaria in Kakamega

```
. regress Malaria Temp Rainfall RH
```

Source	SS	df	MS			
				Number of obs	=	12
				F(3, 8)	=	1.64
Model	2919297.85	3	973099.283	Prob > F	=	0.2556
Residual	4744037.34	8	593004.667	R-squared	=	0.3809
				Adj R-squared	=	0.1488
Total	7663335.19	11	696666.835	Root MSE	=	770.07

Malaria	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Temp	1761.63	1204.647	1.46	0.182	-1016.291	4539.551
Rainfall	-5.26488	7.437219	-0.71	0.499	-22.41514	11.88538
RH	226.7999	151.5196	1.50	0.173	-122.605	576.2047
_cons	-50050.63	35182.16	-1.42	0.193	-131180.8	31079.59

Monthly RH and rainfall in Kakamega County had rising trends while temperature was decreasing towards the end of the year. All climate elements had positive monthly correlation with malaria transmission in Kakamega County. On the other hand, temperature and RH regressed positively with the transmission while rainfall and transmission regressed negatively. From these results, it is temperature that consistently compared with malaria transmission in this area. The study therefore attributed the monthly malaria transmission dynamics in Kakamega County to the influence of temperature which had remained consistently positive at all levels.

[23] recognized malaria as a tropical disease meaning it would thrive best under the tropical climate where temperatures and rainfall are relatively high. According to this study, Kakamega temperature peaks in February. This gives way to the long rains whose onset is March, cyclically setting the most conducive environment for malaria transmitting vectors in May hence the escalated transmissions which come in early or at the middle of every year. These monthly trends confirmed the predictions by [13] of annual seasonality, cyclical patterns and strong but temporally varying trends.

[20] observed a set of transmission windows typical to India in terms of different temperature ranges. [8] strengthened spatial variations. This study established transmission windows defined by temporal variations based on conducive transmission environments monthly created by temperature and rainfall flactuations.

3.1.1.2 Kisumu County

Correlation analysis between spatiotemporal variability of Climate Parameters and malaria transmission in Kisumu County revealed a negative relationship between malaria transmission and temperature (r = - 0.3697), and a negative relationship between malaria transmission and rainfall (r = - 0.3794). The relationship between malaria transmission and RH was however positive (r = 0.1025). Given the two tailed significance test of 0.05, the relationships between malaria transmission and temperature, malaria transmission and RH and malaria transmission and rainfall were not significant. None of these selected climate parameters could thus confidently explain the monthly variability of malaria transmission in Kisumu County (Table 4.21).

Table 3.3: Correlation analysis for Monthly Relationship between Malaria cases and climatic parameters in Kisumu

```
. pwcorr malariaksm TempKsm RainKsm RHKsm, obs sig

             | malari~m  TempKsm  RainKsm    RHKsm
-------------+------------------------------------
  malariaksm |   1.0000
             |
             |       12
             |
     TempKsm |  -0.3697   1.0000
             |   0.2369
             |       12       12
             |
     RainKsm |  -0.3794   0.1991   1.0000
             |   0.2239   0.5349
             |       12       12       12
             |
       RHKsm |   0.1025  -0.6469   0.5503   1.0000
             |   0.7513   0.0230   0.0637
             |       12       12       12       12
```

Regression conducted involving the three selected climatic parameters and malaria transmission revealed positive but not significant relationship between malaria transmission and temperature, positive but not significant relationship between RH and malaria transmission and a negative but not significant relationship between rainfall and malaria transmission. The models were: $Y = -18987.43 + 555.6542X_2$ where Y = cases of confirmed malaria transmission, X_2 = temperature; $Y = -18987.43 + 214.1365X_3$, $X3 =$ RH and $Y = -18987.43 – 23.54156X_1$, $X_1 =$ rainfall. The regression R^2 value of the line of best fit was 29.65% meaning less than half of the observations could be explained by the data (Table 3.4). From such observations, the study again concluded that variability of selected climate elements (rainfall, temperature and RH) could not confidently explain malaria transmission trends in Kisumu County.

Table 3.4: Regression analyses for Monthly Relationship between Malaria cases and climatic parameters in Kisumu

```
. regress malariaksm TempKsm RainKsm RHKsm

      Source |       SS           df       MS      Number of obs   =        12
-------------+----------------------------------   F(3, 8)         =      1.12
       Model |  5039009.34         3  1679669.78   Prob > F        =    0.3953
    Residual |  11953510.3         8  1494188.78   R-squared       =    0.2965
-------------+----------------------------------   Adj R-squared   =    0.0327
       Total |  16992519.6        11  1544774.51   Root MSE        =    1222.4

------------------------------------------------------------------------------
  malariaksm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     TempKsm |   555.6542   1409.808     0.39   0.704    -2695.369    3806.678
     RainKsm |  -23.54156   19.53225    -1.21   0.263      -68.583    21.49988
       RHKsm |   214.1365   253.9267     0.84   0.424    -371.4195    799.6926
       _cons |  -18987.43    45416.8    -0.42   0.687    -123718.8    85743.91
------------------------------------------------------------------------------
```

The climate elements (rainfall and RH) had rising trends while temperature was decreasing. All elements had positive correlations with transmission. Temperature and rainfall had negative regression with transmission while RH and transmission were positive. From these observations, the study took temperature to be the only element that had consistently positive relationship with malaria transmission dynamics in Kisumu County. Like [17] established that transmission rate mostly depended on rainfall, in Kisumu County, monthly malaria transmission was defined by temperature. [11] strengthened the one climatic element determination aspect when he observed that all the three identified climate parameters might simultaneously present an enabling transmission environment while elsewhere, one or two may over - ride others in providing such environments as was the case in Kisumu County where temperature over - rode rainfall and RH to become the chief determinant of malaria transmission.

3.1.1.3. Migori County

In Migori County, the analysis of Monthly Climate Parameters and the monthly total confirmed Malaria Transmission revealed positive relationships between malaria transmission and temperature (r = 0.3076). The correlation was however negative between malaria transmission and RH (r = - 0.1550), and negative between malaria transmission and rainfall (r = -0.2986) (Table 3.5). This implied that Malaria Transmission increased with increase in temperature while it decreased with increase in RH and rainfall. However, considering the 2-tailed test of significance level at 0.05, none of these relationships was found to be significant. At this level of observation, monthly malaria transmission was attributed to temperature although none of the climate parameters confidently explained malaria transmission trends in Migori County.

Table 3.5: Correlation analysis for Monthly Relationship between Malaria cases and climatic parameters in Migori

```
. pwcorr MalariaMig TempMig RainMig RHMig, obs sig
```

	Malari~g	TempMig	RainMig	RHMig
MalariaMig	1.0000			
	12			
TempMig	0.3076	1.0000		
	0.3307			
	12	12		
RainMig	-0.2986	0.2113	1.0000	
	0.3458	0.5098		
	12	12	12	
RHMig	-0.1550	0.7321	0.7290	1.0000
	0.6304	0.0068	0.0071	
	12	12	12	12

In regression, positive and significant relationship was established between total malaria transmission cases and temperature, and a positive but not significant relationship between total malaria transmission and rainfall in Migori County. RH on the other hand had negative but not significant relationship with malaria transmission. These were explained by the following models: $Y = - 2405.911 + 1566.32X_2$ Where Y = Cases of confirmed malaria, X_2 =temperature; $Y = -2405.911 + 3.683698X_1$ Where Y = Cases of confirmed malaria, X_1 = rainfall; $Y = -2405.911 – 469.6379X_3$ Where Y = Cases of confirmed malaria, X_3 = RH. The R^2value was 45.30%. In Migori County, malaria transmission trends were confidently defined by temperature according to regression (Table 3.6).

Table 3.6: Regression analysis for monthly malaria in Migori County

```
. regress MalariaMig TempMig RainMig RHMig
```

Source	SS	df	MS
Model	1778972.14	3	592990.715
Residual	2148417.47	8	268552.184
Total	3927389.61	11	357035.419

Number of obs	=	12
F(3, 8)	=	2.21
Prob > F	=	0.1648
R-squared	=	0.4530
Adj R-squared	=	0.2478
Root MSE	=	518.22

MalariaMig	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TempMig	1566.32	687.032	2.28	0.052	-17.97884	3150.619
RainMig	3.683698	4.451356	0.83	0.432	-6.581147	13.94854
RHMig	-469.6379	261.8471	-1.79	0.111	-1073.458	134.1826
_cons	-2405.911	8474.486	-0.28	0.784	-21948.11	17136.29

The Migori climatic conditions depicted almost similar characteristics to those of Kisumu and Kakamega with small variations among R^2 values. Monthly temperature in Migori County indicated a reducing trend at an R^2 value of 16.03% towards the end of the year. Rainfall increased at an R^2 value of 3.58% while RH increased at R^2 value of 0.22%. Of all these climate elements, it is only temperature that had a positive correlation and regression with malaria, regression being positively significant. From this observation, the decreasing trend of temperature was used to explain the decreasing trend of malaria transmission in Migori County. Once again as was observed by [17] in Korhogo-West Africa where it was established that transmission rate mostly depended on rainfall, in Migori County, monthly transmissions were driven by Temperature.

3.1.2 Relationship between Annual Climatic Elements and Malaria Transmission

During the study period (2011 – 2020), annual relationship between variability in climate parameters (temperature, relative humidity and rainfall) and malaria transmission (morbidity) were established using Pearson's Product Moment correlation coefficient and regression analyses. Following were the observations made.

3.1.2.1 Kakamega County

In Kakamega County, RH values correlated positively (r = 0.105) with malaria transmission. Temperature (r = - 0.054) and rainfall (r = - 0.026) on the other hand had negative correlations with the transmission. Of those relationships, none was significant (Table 3.7).

Table 3.7: Correlation Matrix showing relationship between annual malaria transmission and climate parameters in Kakamega County

Correlations

		MalMum	TempMum	RHMum	RainMum
MalMum	Pearson Correlation	1	-.054	.105	-.026
	Sig. (2-tailed)		.881	.774	.942
	N	10	10	10	10
TempMum	Pearson Correlation	-.054	1	-.690*	-.656*
	Sig. (2-tailed)	.881		.027	.039
	N	10	10	10	10
RHMum	Pearson Correlation	.105	-.690*	1	.215
	Sig. (2-tailed)	.774	.027		.551
	N	10	10	10	10
RainMum	Pearson Correlation	-.026	-.656*	.215	1
	Sig. (2-tailed)	.942	.039	.551	
	N	10	10	10	10

*. Correlation is significant at 0.05 level (2-tailed).

The relationships between rainfall and malaria transmission, and between temperature and malaria transmission in Kakamega County were confirmed to be negative following regression models of, Y = 1445.65 – 2697877X_1 where Y = Cases of malaria transmission, X_1= Rainfall and Y = 1445.65 – 71.18992X_2 (Table 3.8) Where Y = Cases of confirmed malaria, X_2=temperature. RH on the other hand regressed positively Y = 1445.65 + 63.65365X_3 where Y = Cases of malaria transmission, X_3= RH. None of the relationships was significant. The regression R^2 value of the line of best fit was 1.4%. At R^2 value of 1.4% climate parameters confirmed least relationship with malaria transmission trends among the three selected counties of the LLVB, Kenya (Table 3.8).

Table 3.8: Rainfall/Malaria Regression for Kakamega County

Source	SS	df	MS
Model	205160.764	3	68386.9213
Residual	14752777.1	6	2458796.18
Total	14957937.9	9	1661993.1

Number of obs	10
F(3, 6)	0.03
Prob > F	0.9931
R-squared	0.0137
Adj R-squared	-0.4794
Root MSE	1568.1

KKmalaria	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
KKrainfal	-.2697877	2.350906	-0.11	0.912	-6.022247	5.482671
KKtemp	-71.18992	1772.514	-0.04	0.969	-4408.374	4265.995
KKRH	63.65365	408.2107	0.16	0.881	-935.202	1062.509
_cons	1445.656	65774.35	0.02	0.983	-159498.4	162389.7

From the above findings, there were no significant relationships between climate elements and malaria transmission in Kakamega County. Rainfall and temperature negatively correlated with malaria transmission while RH was positive. When regressed, the results were the same as those of correlation. RH trend in Kakamega was rising. From these observations, the study concluded that although correlation and regression results were not significant, and given that all selected climate elements were within malaria transmission limits according to [20], the increase in annual malaria transmission in Kakamega County was attributed to the increase in RH with which it maintained a consistent positive relationship.

3.1.2.2 Kisumu County

Correlation analysis between spatiotemporal variability of Climate Parameters and total Confirmed malaria transmission in Kisumu County revealed a positive relationship between malaria transmission and temperature (r = 0.557), and a positive relationship between malaria transmission and rainfall (r = 0.023). The relationship between malaria transmission and RH was however negative (r = - 0.277). This indicated that higher number of malaria transmission cases occurred when temperature and rainfall were high and vice versa. On the other hand, an increase in RH meant a decrease in malaria transmission. Given the two tailed significance test of 0.05, the relationships between malaria transmission and temperature, RH and rainfall were not significant (Table: 3.9). The implication here was therefore that none of these selected climate parameters could confidently define the annual variability of malaria transmission in Kisumu County.

Table 3.9: Correlation Matrix showing relationship between total confirmed cases of malaria transmission and climate parameters in Kisumu County

Correlations					
		malaKSM	TemKSM	RHKSM	RainKSM
malaKSM	Pearson Correlation	1	.557	-.277	.023
	Sig. (2-tailed)		.095	.439	.949
	N	10	10	10	10
TemKSM	Pearson Correlation	.557	1	-.378	-.264
	Sig. (2-tailed)	.095		.282	.462
	N	10	10	10	10
RHKSM	Pearson Correlation	-.277	-.378	1	.636*
	Sig. (2-tailed)	.439	.282		.048
	N	10	10	10	10
RainKSM	Pearson Correlation	.023	-.264	.636*	1
	Sig. (2-tailed)	.949	.462	.048	
	N	10	10	10	10

*. Correlation is significant at the 0.05 level (2-tailed).

A regression was conducted involving the three selected climatic parameters and malaria transmission. The result was a positive but not significant relationship between malaria transmission and temperature, a positive but not significant relationship between rainfall and malaria transmission while a negative but not significant relationship between RH and malaria transmission. The models were: Y = -383.77 + 1.66X_1 where Y = cases of confirmed malaria transmission, X_1 = rainfall; Y = -383.77 + 2317.46X_2, X_2 = temperature and Y = -383.77 + 2317.46X_3, X_3 = RH. The regression R^2 value of the line of best fit was 40% meaning less than half of the observations could be explained by the data. From such observations, the study concluded that the selected climate parameters (rainfall, temperature and RH) could not confidently be used to explain annual malaria transmission trends in Kisumu County.

The study established that all the climate elements were increasing in Kisumu County. When correlated with malaria transmission, temperature and rainfall had positive correlations with the transmission while RH was negative. Regression result was the same as that of correlation (Table 3.10). The study thus attributed the annual increase of malaria transmission in Kisumu County to that of temperature and rainfall though the relationships were not significant. This observation still supported that of [17] where only one element (rainfall) was responsible for defining the transmission trends in Korhogo-West Africa.

Table 3.10: Annual Climate/Malaria Regression for Kisumu County

```
. regress KSMmalaria rainfall Temp RH

      Source |       SS           df       MS      Number of obs   =        10
-------------+----------------------------------   F(3, 6)         =      1.28
       Model |  8553809.84         3  2851269.95   Prob > F        =    0.3628
    Residual |  13348034.9         6  2224672.49   R-squared       =    0.3906
-------------+----------------------------------   Adj R-squared   =    0.0858
       Total |  21901844.7         9  2433538.31   Root MSE        =    1491.5

------------------------------------------------------------------------------
  KSMmalaria |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    rainfall |   1.656705   1.923272     0.86   0.422    -3.049373    6.362783
        Temp |   2317.462    1485.93     1.56   0.170    -1318.478    5953.402
          RH |  -261.6951     375.01    -0.70   0.511    -1179.311    655.9212
       _cons |  -38343.77    46126.3    -0.83   0.438    -151210.8    74523.23
------------------------------------------------------------------------------
```

3.1.2.3 Migori County

In Migori County, the analysis of Climate Parameters and the total confirmed malaria transmission revealed positive relationships between malaria transmission and temperature (r = 0.147) and between malaria transmission and RH (r = 0.004) while a negative relationship between malaria transmission and rainfall (r = -0.442) (Table 4.29). This implied that the higher the temperature and RH, the higher the malaria transmission. Malaria transmission on the other hand decreased with increase in rainfall. However, considering the 2-tailed test of significance level at 0.05, none of these relationships was significant. None of the climate parameters thus confidently explained malaria transmission trends in Migori County. Malaria transmission though on the decrease remained high with little influence from the varying climate parameters. The underlying parameters remained optimal and hardly went beyond the transmission thresholds.

All climate elements in Migori County had increasing trends. When correlated, malaria transmission correlated positively with temperature and RH whereas it correlated negatively with rainfall. In regression, RH and rainfall regressed negatively with malaria transmission. Temperature on the other hand was positive with malaria transmission (Table 3.11). From these results, it was only rainfall that was consistent in its relationship with transmission. The study therefore attributed the decreasing trends of annual malaria transmission in Migori County to increase in rainfall. This was a case that greatly resembled that of [17] in Korhogo-West Africa where transmission was mostly defined by rainfall.

Table 3.11: Correlation Matrix showing relationship between total confirmed cases of malaria transmission and climate parameters in Migori County

Correlations

		MalaSONY	TempSONY	RHSONY	RainSONY
MalaSONY	Pearson Correlation	1	.147	.004	-.442
	Sig. (2-tailed)		.685	.992	.201
	N	10	10	10	10
TempSONY	Pearson Correlation	.147	1	.690*	.409
	Sig. (2-tailed)	.685		.027	.240
	N	10	10	10	10
RHSONY	Pearson Correlation	.004	.690*	1	.223
	Sig. (2-tailed)	.992	.027		.536
	N	10	10	10	10
RainSONY	Pearson Correlation	-.442	.409	.223	1
	Sig. (2-tailed)	.201	.240	.536	
	N	10	10	10	10

*. Correlation is significant at the 0.05 level (2-tailed).

When regressed, a positive but not significant relationship was established between malaria transmission and temperature in Migori County. RH and rainfall on the other hand had negative relationships with malaria transmission. These were explained by the following models: $Y = -11238.41 + 1029.763X_2$ Where Y = Cases of confirmed malaria, X_2 =temperature; $Y = -11238.41 – 97.14876X_3$ Where Y = Cases of confirmed malaria, X_3 = RH and $Y = -11238.41 – 1.812504X_1$ Where Y = Cases of confirmed malaria, X_1 = rainfall. The R^2value was 3.5% (Table 3.12).

In Migori County, variability of annual malaria transmissions were not confidently defined by the selected climate parameters since less than half of the observations were defined by the data in question.

Table 3.12: Climate/Malaria Regression for Migori County

```
. regress MigoriMalaria Migorirain Migoritemp MigoriRH

      Source |       SS           df       MS      Number of obs   =        10
-------------+----------------------------------   F(3, 6)         =      1.12
       Model |  5755539.11         3  1918513.04   Prob > F        =    0.4130
    Residual |  10294150.2         6  1715691.71   R-squared       =    0.3586
-------------+----------------------------------   Adj R-squared   =    0.0379
       Total |  16049689.4         9  1783298.82   Root MSE        =    1309.8

------------------------------------------------------------------------------
MigoriMala~a |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  Migorirain |  -1.812504   1.049473    -1.73   0.135    -4.380473    .7554651
  Migoritemp |   1029.763   863.0306     1.19   0.278    -1081.997    3141.523
    MigoriRH |  -97.14876    171.893    -0.57   0.592    -517.7558    323.4583
       _cons |  -11238.41   14016.05    -0.80   0.453    -45534.46    23057.64
------------------------------------------------------------------------------
```

In all the above cases, climate malaria transmission relationships depicted the findings made by [2] that Malaria is one of the few climate – sensitive health outcomes that has been subjected to thorough global and regional assessments using a range of malaria impact models and climate scenarios with varying results. The correlation and regression results in Kakamega, Kisumu and Migori always varied and almost all were insignificant leaving none to confidently explain malaria transmission monthly and annually. However, the insignificant outcomes could be explained by the fact that the climatic conditions were most of the times within malaria transmission ranges as was explained by [12] hence the observed insignificant impacts during the malaria transmission periods.

3.2 Combined Relationships in the Entire LLVB, Kenya in Steps

All the selected climatic parameters had no significant relationship with malaria transmission at the sampled altitudes except temperature that had a positive significant regression with monthly malaria transmission in Migori County (P = 0.052). However, at an R^2 value of 45.3%, this could have been a factor of chance.

As [1] argued, for most *anopheles* vector species that transmit malaria, the optimal temperature range must be within 20^0C to 30^0C. This should extend over a period for completion of sporogeny. According to that study, malaria transmission also depends on seasons with rainy period being preferred for vector multiplication. RH should neither be below 55% nor above 80%. Exceeding those limits, it becomes lethal for mosquitoes' survival. The three climate elements are the major climatic determinants of malaria transmission.

Studying spatiotemporal variation of temperature, RH and rainfall in the sampled counties of LLVB, it was established that in Kakamega County, temperature varied between 23.58^0C and 21.69^0C during the study period. Rainfall varied between 2823.7mm and 1674.4mm while RH varied between 68.96% and 64.42%. In Migori County, temperature varied between 24.12^0C and 21.04^0C. Rainfall varied between 2906.2mm and 1424.3mm while RH varied between 72.22% and 62.17%. The situation in Kisumu County was almost the same as temperature varied between 24.63^0C and 23.21^0C, rainfall varied between 2125.9mm and 981.0mm, RH varied between 62.96% and 56.33%. From these findings, climate parameters operated within malaria transmission thresholds in all the sampled counties and although malaria transmission levels varied significantly among the counties, the variations could not have been confidently defined by climate elements whose variations remained optimal and hardly went beyond malaria transmission limits.

Due to the fact that none of the relationships between climate and malaria transmission in all the sampled counties were significant, they could not be used to give substantive conclusions on spatiotemporal malaria transmission variability. The study thus decided to explore further investigative mechanisms in steps as follows:

3.2.1 Correlation of Malaria Transmission, Temperature, Rainfall, RH and Altitude

Pearson's correlation analysis for the entire LLVB, Kenya revealed that Malaria transmission was negatively affected by Relative Humidity and altitude. This was a significant outcome with RH (r = -0.461, P = 0.01) and Altitude (r = -0.475, P = 0.008) (Table 3.13). The significance observed in RH could have been a factor of figures from one or two counties overcoming the others in the process of combination from different altitudes hence elevating RH to become a significant climatic determinant in the entire LLVB, Kenya. This outcome supports the proposal of the study that large - scale climatic occurrences do affect the micro – scale occurrences differently. This undermined blanket assumption.

Table 3.13: Correlation result for the effect of temperature, relative humidity, rainfall and altitude on malaria in the entire LLVB, Kenya (2011 – 2020)

Correlations

		Malaria	RH	Temp	Rainfall	Altitude
malaria	Pearson Correlation	1	-.461*	.208	-.227	-.475**
	Sig. (2-tailed)		.010	.271	.229	.008
RH	Pearson Correlation	-.461*	1	-.388*	.532**	.872**
	Sig. (2-tailed)	.010		.034	.002	.000
Temp	Pearson Correlation	.208	-.388*	1	-.464**	-.436*
	Sig. (2-tailed)	.271	.034		.010	.016
Rainfall	Pearson Correlation	-.227	.532**	-.464**	1	.368*
	Sig. (2-tailed)	.229	.002	.010		.046
Altitude	Pearson Correlation	-.475**	.872**	-.436*	.368*	1
	Sig. (2-tailed)	.008	.000	.016	.046	
	N	30	30	30	30	30

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

3.2.2 Regression of Malaria Transmission, Temperature, Rainfall and RH

Overall regression result for the combined total malaria case transmission in the lake region and combined climate parameters (Relative humidity, temperature and Rainfall) during the period 2011 – 2020, were evaluated. The result showed that in the lake region during the year 2011 – 2020, a number of malaria transmission cases were positively affected by temperature and rainfall. The cases were affected negatively by the relative humidity. Effects were shown by R^2 value of 19.61% in a regression model equation $Y = 5448.22 + 228.299X_1 + 0.0272X_2 – 117.896X_3$ (Where Y = Malaria cases in the region, X_1 = temperature, X_2 = rainfall, X_3 = relative humidity (Table 3.14). This overall effect indicated that malaria transmission increased with increase in temperature and rainfall. However, decrease in relative humidity resulted into an increase in malaria transmission. None of these results was significant.

Table 3.14: Regression result for the effect of temperature, relative humidity and rainfall on malaria in the region (2011 – 2020)

Source	SS	df	MS
Model	13636128.8	3	4545376.27
Residual	55891224.8	26	2149662.49
Total	69527353.6	29	2397494.95

Number of obs	= 30
F(3, 26)	= 2.11
Prob > F	= 0.1227
R-squared	= 0.1961
Adj R-squared	= 0.1034
Root MSE	= 1466.2

Malaria	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RH	-117.896	60.83847	-1.94	0.064	-242.9513	7.159235
Temp	228.2998	391.5903	0.58	0.565	-576.6257	1033.225
Rainfall	.0271715	.6902272	0.04	0.969	-1.391611	1.445954
_cons	5448.22	10834.69	0.50	0.619	-16822.8	27719.24

From these observations, the study adopted the hypothesis, "There is no significant relationship between variability in climate parameters and malaria transmission in different altitudes of the LLVB, Kenya". The insignificant correlations implied that the observed relationships might have occurred on account of chance and could not be used to make any significant conclusions regarding the relationship between climate and malaria transmission in different altitudes of the LLVB, Kenya. It must however be born in mind that although the relationships were not significant, climatic elements remained optimal for malaria transmission in the LLVB throughout the study period. This could make the relationships remain insignificant.

3.2.3 Regression of Malaria Transmission, Temperature, Rainfall, RH and Altitude

Overall effects of the climatic conditions on malaria transmission were further evaluated using stepwise linear regression. The finding showed that only altitude had a significant effect on spatiotemporal malaria transmission variability with a regression R^2 value of 22.6% (Table 3.15). The effect of the altitude adopted the equation model of; Y = Constant + $\beta_1 X_1$. Where Y = Malaria cases in the region, X_1 = altitude, β_1 is the gradient of X_1 on Y. Y = 9593.413 – 5.060X_1 (Table 3.16).

Table 3.15: Stepwise Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.475[a]	.226	.198	1386.75274

a. Predictors: (Constant), Altitude

Table 3.16: Stepwise linear Regression Results

Model		Unstandardized Coefficients	Standardized Coefficients			
		B	Std. Error	Beta	t-value	Sig.
	(Constant)	9593.413	2273.925		4.219	.000
1	Altitude	-5.060	1.772	-.475	-2.856	.008

a. Dependent Variable: malaria

Effects of other climatic parameters were eliminated during computation (Table 3.17). This left only altitude as the major determinant of malaria transmission variability in the study area. This outcome confirmed the observation made by [5] that transmission differs by altitude such that the higher the altitude, the lower the transmission. The study thus zoned LLVB, Kenya into altitudes according to transmission levels: 1001m to 1200m – high transmission zones; 1201 to 1400 - medium transmission zones; 1401 to 1600 – low transmission zones.

Table 3.17: Zones of malaria transmission in the LLVB

Altitude (m)	Zone	Description
1001 – 1200	Zone 1	High transmission level
1201 – 1400	Zone 2	Medium transmission level
1401 - 1600	Zone 3	Low transmission level

In line with the argument raised by [5], this study revealed that climate parameters operated within malaria transmission thresholds at all the sampled altitudes of the LLVB, Kenya. Although transmission levels varied significantly among the sampled altitudes, they might not have been effectively defined by the optimal climate variations. Spatial malaria transmission was thus defined by altitude while temporal malaria transmission was insignificantly defined by temperature as was seen in the monthly transmissions. [27] confirmed endemic transmission due to the optimal climate factor, and given the temperature (20^0C - 30^0C) and RH (55% - 80%) transmission ranges, transmission is likely to continue, and even rise at differing altitudes of the LLVB, Kenya.

IV. DISCUSSION

The relationship between malaria morbidity and climate elements, in Kakamega, Kisumu and Migori significantly varied. Almost all the relationships were insignificant leaving none of the climate elements to confidently explain spatiotemporal variability in malaria transmission both monthly and annually. It was only temperature that had a positive significant regression with monthly malaria transmission in Migori County (P = 0.052). At an R^2 value of 45.3%, this could have been a factor of chance. From these observations, the researcher adopted the hypothesis, "There is no significant relationship between variability in climate parameters and malaria transmission in different altitudes of the LLVB, Kenya". As [1] argued, for most *anopheles* vector species that transmit malaria, the optimal temperature range is within 20^0C to 30^0C. This should extend over a period for completion of sporogeny. Air temperature below 18^0C and 15^0C prohibit development of *P. falciparum* and *P.Vivax* respectively [15]. [18] places the upper transmission limit at a maximum of 25^0C. This decreases as temperature rises to 28^0C. Beyond these thresholds, survival of both the parasites and the mosquitoes is threatened. Transmission then ceases. [1] further emphasizes that transmission also depends on seasons with rainy period being preferred for vector multiplication. RH should neither be below 55% nor above 80%. According to [14], cases of malaria were bound by RH at minimum of 20-30% and maximum of 85%. Exceeding those limits, it becomes lethal for mosquitoes' survival hence diminished malaria transmission.

The insignificant correlations implied that the observed relationships might have occurred on account of chance and could not be used to make any substantive conclusion regarding the relationship between climate and malaria transmission in different altitudes of the LLVB, Kenya. However, there was indication that transmission in Kakamega was defined by RH, in Kisumu by temperature and rainfall, while in Migori, by rainfall. All these were not significant observations.

In line with the argument raised by [1], this study revealed that climate parameters operated within malaria transmission thresholds at all the sampled altitudes of the LLVB, Kenya, and although transmission levels varied significantly among the sampled counties, malaria transmission variations might not have been defined by climate variations which remained optimal and hardly went beyond the transmission limits. [26] confirmed that malaria transmission endemically depended on the three climatic elements. Given the temperature (20^0C - 30^0C) and RH (55% - 80%) transmission ranges as defined by [1], malaria transmission is still likely to continue, and to rise in many parts of the LLVB, Kenya unless some remedial measures are emphatically put in place to check the transmission levels.

When data from all the sampled counties was put together, the result indicated that in the LLVB, Kenya, spatiotemporal variability of malaria transmission was positively affected by temperature and rainfall. Using stepwise linear regression, the findings established that only altitude had a significant effect on spatiotemporal malaria transmission variability. LLVB, Kenya was thus zoned into the following transmission zones according to altitude and transmission levels: 1001m to 1200m – high transmission zones; 1201 to 1400 - medium transmission zones; 1401 to 1600 – low transmission zones. When predicted, it was established that malaria transmission in high and medium zones will be increasing while it will be decreasing in the low transmission zones. This was an indication that with climate change, transmission is likely to increase towards the low transmission areas.

V. CONCLUSION

The three climate parameters that are the major determinants of malaria transmission each affected transmission differently but none of the effects was significant in different altitudes of the LLVB, Kenya. Mean temperature of 22.95^0C, Mean RH of 64.46% and Mean annual rainfall of 1844.57mm were well within the transmission limits for both vector and parasite survival. That made it difficult to significantly impact their varying effects on malaria transmission. It was only in Migori County that a significant relationship occurred when temperature and monthly malaria transmission were regressed. This might have just been a factor of chance being that the R^2 value was below 50% (45.3%) according to Descriptive Time Series analysis.

In a stepwise assessment combining data from all the sampled areas, a regression revealed that malaria transmission had a positive but not significant relationship with temperature and rainfall. This translated into a negative relationship between malaria transmission and altitude – It was established that the higher the altitude the lower the transmission in the entire LLVB, Kenya. This was confirmed using a further regression where all climate variables were eliminated leaving only altitude as the major determinant of variability of malaria transmission in the study area. It was therefore not right to make umbrella assumptions about malaria transmission in the LLVB, Kenya without knowledge of the influence of varying altitudes.

From the outcomes, increase or reduction of malaria transmission in different altitudes of the LLVB, Kenya was not defined by climate variability. LLVB, Kenya was thus considered one of the areas confirming the uncertainties regarding the factors driving the increase or reduction in malaria transmission in Kenya..

VI. RECOMMENDATION

Interventions on malaria transmission should consider the different transmission rates at different altitudes since transmission varies by altitude - the lower the altitude, the higher the transmission and the higher the need for attention. With evidence that there is climate change, meteorological information will help to enhance surveillance processes. On that note, Meteorologists and the Medics should continue collaborating to monitor any adverse effects that may arise from climate variations. In order to effectively manage malaria transmission in the LLVB, Kenya Meteorologists should play the role of production with the Medics being consumers of the meteorological products - climate. Given that all the selected areas met the malaria transmission thresholds, there is need to find out why some parts should experience upsurge while others like Migori County are experiencing reduction. Migori case should be investigated and findings used to enhance reduction with an aim of eradication in Migori and other Counties.

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