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Spatiotemporal distribution of rift valley fever and malaria vectors in Baringo County, Kenya: Implications on vector control

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Abstract
Rift Valley Fever and malaria are zoonotic and human diseases respectively that pose major production and health challenges to pastoralists. This study aimed to determine the spatiotemporal distribution of mosquito vectors of these two diseases in Baringo County, Kenya. A longitudinal study design was used to collect mosquitoes from twenty four sites. Rainfall seasonality was determined using rainfall data from the WorldClim database. Negative binomial and zero-inflated negative binomial regression models were used to determine the effect of rainfall seasonality and ecogeographical conditions on vector distribution. Spatio-temporal maps showing vector distribution were made using the *sf* package in R. Four Rift Valley Fever vector species and four malaria vector species were collected and were predominantly found in the lowland and riverine zones. Vector control interventions against the two diseases should therefore target these two zones. The study also recommends integrated vector management methods targeting both larval and adult stages.

Keywords: Malaria, mosquitoes, rainfall seasonality, Rift Valley Fever, spatiotemporal distribution, vector control

Introduction
Rift Valley fever (RVF) and malaria are vector-borne diseases caused by the Rift Valley fever virus (RVFV) (Bunyaviridae: Phlebovirus) and *Plasmodium* parasite respectively [1, 2]. Four Plasmodium species are known to cause malaria in humans, namely *Plasmodium falciparum*, *P ovale*, *P malariae*, and *P vivax* with *P. falciparum* and *P. vivax* being responsible for most malaria cases [2].

RVF poses a threat to human and animal health and drastically reduces animal production. In animals, it causes high mortality in new-borns and mass abortion in pregnant animals causing massive economic losses [1, 3]. RVF was initially described in Kenya in 1930 and recurrent RVF epizootics have since been reported in countries in eastern and southern Africa, West Africa, North Africa, Madagascar, Mayotte, Comoros Islands, Saudi Arabia, and Yemen [4]. The first RVF outbreak occurred in Baringo County between October 2006 and March 2007 and caused human and animal mortalities leading to massive economic losses [3, 5, 6].

Despite the massive resource investment towards the control of malaria, the disease still affects millions of people in the world causing death and morbidity, especially in sub-Saharan Africa. In the year 2018, there were 228 million malaria cases reported worldwide, with mortality of 405,000. Africa carried the majority of the global malaria burden with 93% of the global malaria cases and 94% of the global deaths [7]. In Kenya, malaria is among the leading causes of morbidity with approximately 3.5 million new clinical cases and 10,700 deaths each year [8]. Approximately 70% of the Kenyan population is at risk of malaria which accounts for 19% of outpatient consultations [9]. Baringo County lies in the seasonal malaria transmission epidemiological zone that experiences short periods of intense malaria transmission during the rainy season with a malaria prevalence of between 1-5% [9].

Studies have reported relationships between climatic factors and RVF and malaria outbreaks stemming from the effect of climatic factors on the development of mosquito vectors. RVF epidemics are linked to floods that follow heavy rainfall in the wet seasons which leads to the hatching of RVFV infected Aedes mosquitoes that primarily transmit the virus to livestock [10].

Peaks in malaria transmission are linked to seasonal changes in rainfall and temperature that affect the emergence of malaria vectors. An increase in malaria incidence with time lags of between 2 to 4 months after the onset of rainfall and 0 to 1 months after an increase in temperature has been reported [11, 12]. Temperature influences mosquito development and the rate of sporogenic development of *P. falciparum* in mosquitoes [13]. The spatio-temporal variation in climatic factors that regulate vector and parasite development does therefore result in a variation of vector abundance and disease transmission dynamics.

Although vector control is highly effective in preventing vector-borne disease transmission, the full potential of its benefits is yet to be realised in eradication of diseases. Compared to drugs and vaccines, vector control has greatly contributed to eradication of some vector-borne diseases, for example the use of sterile insect technique against tsetse flies in Zanzibar [14]. RVF control is still plagued with challenges, vector control is difficult to implement and vaccines are only available for animals [15, 16]. Malaria control emphasis has been placed on infection management using artemisinin-based combination therapies [17] and vector control using long-life insecticide-treated nets (LLITNs), indoor residual spraying (IRS), and larval source management (LSM) [17, 18]. However, the emergence of artemisinin resistance and insecticide resistance in plasmodium and mosquito populations is of concern to malaria control [19, 20].

Vector control is now focused on integrated vector management (IVM) which provides a conceptual framework for the deployment of cost-effective and sustainable methods of vector control. IVM allows for full consideration of the complex determinants of disease transmission, local disease ecology, anthropogenic risk factors and the socioeconomic status of affected communities [21]. Comprehensive knowledge of vector biology, vector parasite interaction and spatiotemporal distribution of both vector and pathogen are key to improving IVM approaches for vector control and disease eradication [20, 22].

The aim of this study was to determine the spatiotemporal distribution of RVF and malaria vectors, specifically, the seasonal variation in the distribution of mosquito vectors across different ecogeographical zones. Results of the study are presented with an inference on the benefits of a transdisciplinary approach towards the concerted control of RVF and malaria vectors in identified transmission foci. The benefits of such an approach include cost-effectiveness, a reduction of vector population densities and reduced transmission and infection rates leading to a healthy population and increased animal productivity.

Materials and Methods

The study area

The study was carried out in Baringo County, Kenya, which lies between longitudes 35.5968^0 E and 36.2338^0 E, and latitudes 0.1218^0 N and 0.8558^0 N. It is part of the semi-arid zones of Kenya and is inhabited by resource-poor pastoralist communities. The area has poor infrastructure and experiences a harsh climate characterized by low rainfall and high temperatures (Ojwang, Agatsiva and Situma, 2010). This area is prone to VBDs like malaria, RVF, leishmaniasis, and yellow fever. which not only cause morbidity and mortality in humans but in the case of zoonoses also cause animal deaths leading to serious economic losses.

The study area was divided into four zones based on hydrology, altitude, vegetation cover, soil types and precipitation The four zones from east to west were a low-altitude zone surrounding the permanent water bodies with an altitude of below 1,000 m above mean sea level, a mid-altitude zone with an altitude of between 1,000 - 1,500 m above mean sea level, a highland zone with an altitude between 1,500 - 2,300 m above mean sea level and a riverine zone bordering the Kerio River with an altitude of 1,100 - 1,200 m above mean sea level.

The permanent water bodies in the lowland zone are Lake Baringo, Lake 94, and Lake Bogoria. This area receives an annual rainfall of about 600 mm and has a slope of less than 4% with poorly drained soils, making it prone to seasonal flooding. The main vegetation cover is the invasive *Prosopis juliflora* locally known as the mathenge tree.

The mid-altitude area is interspaced with dry riverbeds (lagas) that flow only after the heavy seasonal rains in the Tugen Hills. The slope here is between 20 and 30% and the main vegetation cover is *Acacia* and *Commiphora* bushes.

The highland area comprises of the Tugen Hills. This area has very well-drained soils that support indigenous forests as well as planted exotic forests that grow on the generally steep terrain that has a slope range of 30-40%. Rainfall ranges between 1,000 and 1,500 mm per annum.

The riverine zone borders the Kerio River and has several oxbow lakes, the prominent one being Lake Kamnarok. This zone is prone to flooding because the elevation of the slope is less than 6%.

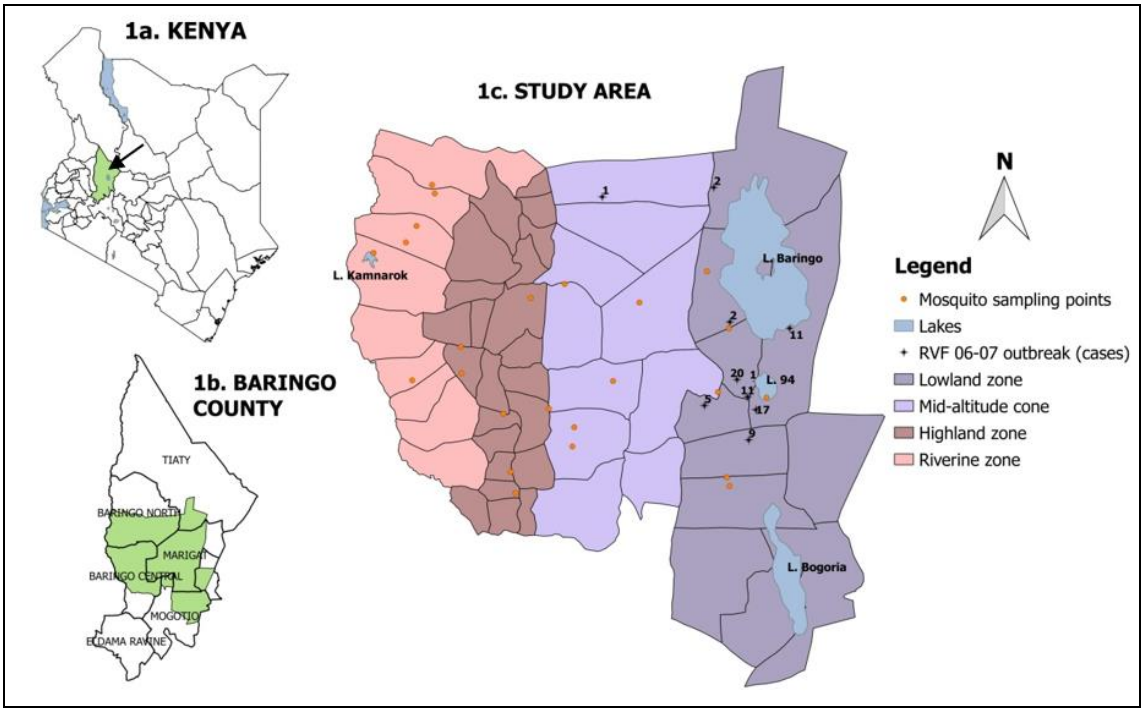

Fig 1: Map of the study area. (1a) Location of Baringo County within Kenya, (1b) the sub-county administrative units within Baringo County with the study area shaded out green, and (1c) the ecological zones within the study area, sampling sites and the 2006-2007 RVF outbreak points.

Research design and sampling procedure

Mosquitoes were sampled based on a longitudinal study design where mosquito samples were collected monthly from 24 randomly selected sites within the study area (six sites per zone). Purposive sampling technique was used to identify mosquito sampling points. The random points tool in Quantum GIS software (Quantum GIS Development Team, 2016) was used to generate 100 random points. These points were converted to a Keyhole Markup Language file (. KML) and exported into Google Earth to help in the identification of points that were close to water bodies and easily accessible by road. Six sites situated near water bodies like lakes, springs, rivers, pan dams, and irrigation canals were chosen in each of the four zones making a total of 24 sampling sites (Figure 1c). Monthly sampling expeditions were conducted during which adult mosquitoes were collected from the 24 sites. The spatial coordinates of all sampling points were recorded to enable spatial analysis.

Adult mosquitoes were collected between June 2015 and April 2016 Adult collections were done indoors and outdoors. Indoor sampling was done from houses near the breeding sites using pyrethrum spray catches made up of 10 ml pyrethrin dissolved in 5 litres of kerosene. Spraying was done in the morning between 06:00 and 08:00 h. White sheets were spread inside the house before spraying. Ten minutes after spraying, dead and immobilized mosquitoes were collected from the sheets. Outdoor collections were done using CDC light traps that were set overnight, between 18:00 and 06:00 h. The collected mosquitoes were brought back to the field laboratory for identification using dichotomous taxonomic keys (23). After identification, known RVF and malaria vectors were grouped into two categories either as RVF or malaria vectors. Collections from each month were then grouped as having been collected from the rainy season or the dry season.

Determining climate seasonality

Climate seasonality was determined using rainfall data of the study area between January 2015 and December 2016 obtained from the WorldClim database [24]. This dataset contains historical climate data from 1969 to 2018 available as raster files and has three variables namely minimum temperature (°C), maximum temperature (°C) and precipitation (mm). The geographical coordinates of the sampling points were used to extract point data from the raster files. Spatial averages were then determined by points data across each ecogeographical zone to produce a 24-month time series of rainfall data. Monthly anomalies of the time series were calculated by subtracting the monthly rainfall values from the 24-month average. Months with a positive anomaly were classified as belonging to the rainy season, while those that had a negative anomaly value were determined as belonging to the dry season.

Data analysis

Distribution of mosquitoes across zones

For each category of vectors, a GTest was performed using the R statistical package to test the null hypothesis that the distribution of individual vector species across the four ecogeographical zones was the same.

Testing spatio-temporal variation in the abundance of RVF and malaria vectors

To choose the best model for analysing the spatiotemporal variation of vectors exploratory data analysis was done to determine the distribution of the data and the presence of overdispersion. The distribution of the data was determined by plotting histograms for both the RVF and malaria datasets. Overdispersion was tested using the dispersiontest function of the AER library in R.

To test the seasonal distribution of the vectors across the eco-geographic zones, negative binomial (NB) regression and

zero-inflated negative binomial (ZINB) regression analyses were used. The ZINB model is a two-part model that uses a negative binomial regression and a logistic regression. Through the negative binomial part, the ZINB can test the effect of the predictors on the frequency of the vectors while the logistic part can test the effect of the predictors on the presence or absence of the vectors. The predictor variables used in the models were ecogeographic zones and season of vector collection. Ecogeographic zones had four levels while season had two levels. Between them, the regressors accounted for environmental and climatic factors associated with vector ecology. The Vuong test function in the pscl package of R was used to compare the performance of a negative binomial (NB) regression model to a zero-inflated negative binomial (ZINB) regression model.

Spatio-temporal maps showing the distribution of RVF and malaria vectors were developed using the sf package in R. The study performed GTest to determine if there was a difference in the spatiotemporal distribution of RVF and malaria vectors across zones and seasons. The null hypothesis tested was that the distribution of RVF and malaria vector species across the four ecogeographical zones was the same. Choropleths depicting the seasonal distribution of RVF and malaria vector were developed using vector counts scaled to natural Jenk breaks implemented by Fisher-Jenks algorithm in R.

Ethical statement

The study acquired both national and the World Health Organization (WHO) ethical clearance referenced P70/02/2013 and Protocol ID B20278 respectively. Consent was sought from the house owners before the spraying exercises commenced.

Results

Climate seasonality

Rainfall in the study area was trimodal. The rainy months spanned from April to May, July – August and November – December, while the dry months were January – March, June, and September –October (Figure 2). For regression analyses, mosquito samples collected during the dry months were classified as collected in the dry season and those collected during the rainy months were classified as collected in the rainy season.

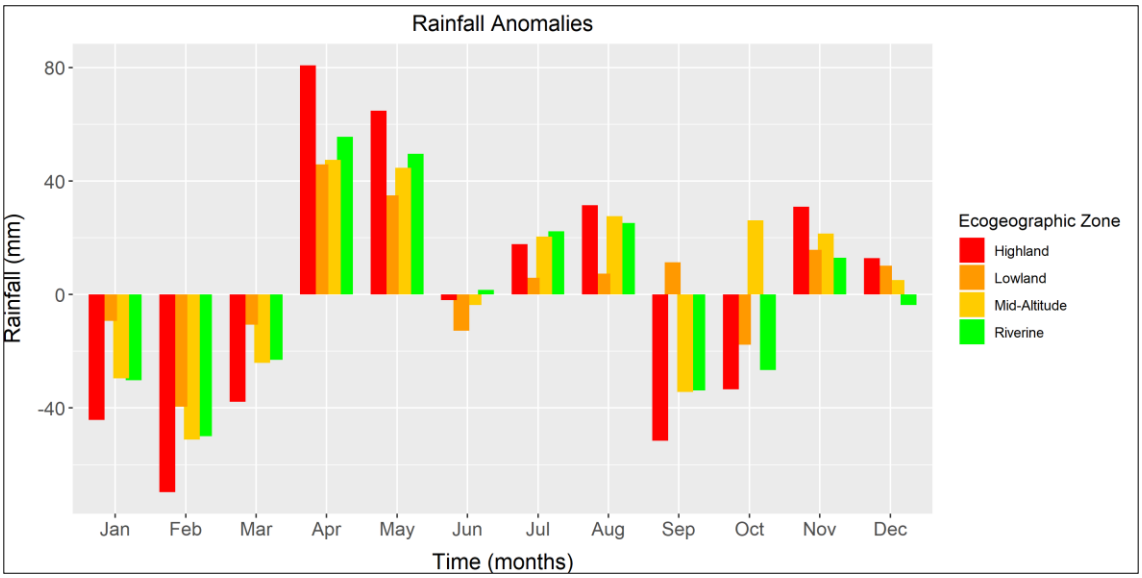

Fig 2: Rainfall anomalies in the eco-geographical zones. Months with negative anomalies received less than the annual average rainfall while those with positive rainfall anomalies received more than the average annual rainfall.

Collected mosquitoes

A total of 12,186 adult mosquitoes were collected from the study area. The identified mosquitoes belonged to 35 species from 9 genera. Collected RVF vectors included *Culex pipiens* s.l. (3,985 adults), *Culex univitattus* (278 adults), *Mansonia africana* (397 adults), and *Mansonia uniformis* (543 adults). *Cx. pipiens* s.l. was collected from 19 sites, *Cx. univitattus* from 16 sites, *Ma. africana* from 14 sites and *Ma. uniformis* from 17 sites. Collected malaria vectors included *Anopheles gambiae* (5410), *Anopheles pharoensis* (283), *Anopheles coustani* (325) and *Anopheles funestus* (69 adults) which transmit malaria. The distribution of the vectors across the eco-geographical zones is given in Table 1. GTests for equal distribution of RVF and malaria vectors across the eco-geographical zones showed that the vectors were not equally distributed ($G = 644.39$, X-squared df = 9, p-value < 0.001 and $G = 235.41$, X-squared df = 9, p-value < 0.001 respectively.)

Table 1: The spatial distribution of RVF and malaria vectors across eco-geographical zones in the study area.

Species	Lowland	Mid-altitude	Highland	Riverine	Disease transmitted
Culex pipiens s.l.	3652	197	197	132	RVF
Culex univitattus	164	5	5	107	RVF
Mansonia africana	297	2	2	95	RVF
Mansonia uniformis	359	39	39	137	RVF
An. coustani	296	7	0	22	Malaria
An. funestus	12	0	0	57	Malaria
An. gambiae	4292	40	25	1053	Malaria
An. pharoensis	269	0	0	14	Malaria

Regression analysis of the vector count data

Histograms of the frequency distribution of RVF and malaria data collected from the study showed the data was zero-inflated and right-skewed, and could not be analysed by methods that assume normality of data. This is depicted by bar plots plotted using natural Jenk breaks as bins for the

count categories (Figure 3). The data was also overdispersed as the variances were significantly greater than the means for RVF data (z = 2.7216, p-value = 0.003248, overdispersion estimate = 63.41), and malaria data (z = 2.68, p-value = 0.00368, overdispersion estimate = 181.242).

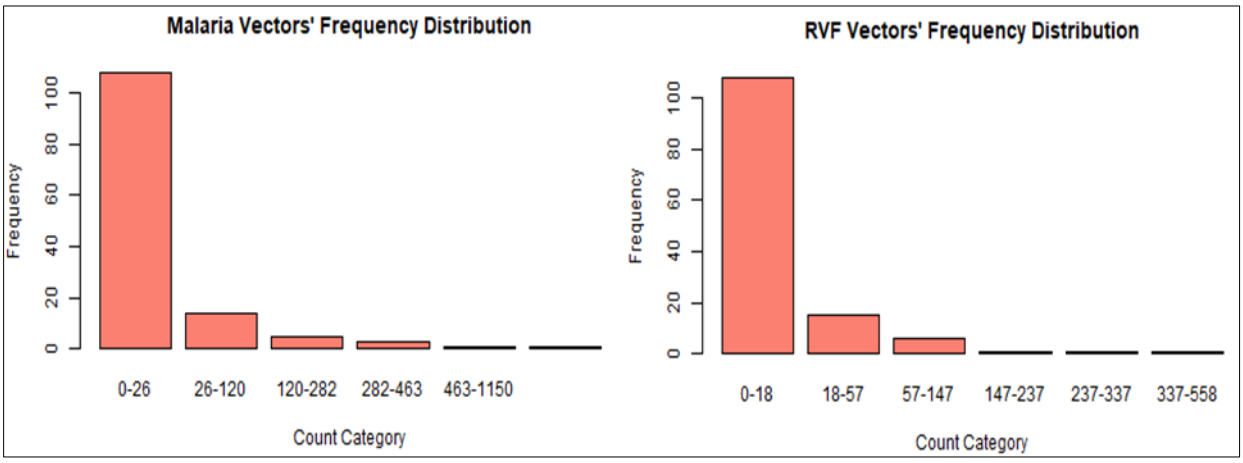

Fig 3: Frequency distribution plots malaria and RVF vectors. Exploratory data analysis revealed that the vector frequency distribution was zero-inflated.

Reggression models for RVF vectors

The NB model for the RVF data showed that the lowland and midaltitude zones, and the rainy season had significant coefficients, and therefore, significantly influenced the distribution of the RVF vectors (Table 2). The highland zone and the dry season served as the reference groups. The incident rate ratios for the occurrence of RVF vectors were obtained by exponentiating the coefficients obtained from the NB model. The incident rate ratio for the occurrence of RVF vectors in the lowland zone was 5.3 times more (p = 0.001) than in the highland zone and 0.07 times more in the midland zone compared to the highland zone ($p < 0.0001$). RVF vector occurrence was 2776 times more (exp 7.2929) in the rainy season compared to the dry season (p = 0.023).

The ZINB model predicted significant effects for lowland and midland zones but with different coefficients. However, the effect of the rainy season was not significant for this model (Table 2). The coefficients of the binomial component of the ZINB model were all non-significant.

Table 2: Regression coefficients for the three regression models performed to test the effect of ecogeographic zones and seasons on the distribution of RVF vectors. The levels of significance are indicated by asterisks where '***' = p-value < 0.0001 and '*' = p-value <0.05.

Coefficients	NB Model		ZINB Model: Count model coefficients (negbin with log link)	
	Estimate	Pr(>|z|)	Estimate	Pr(>|z|)
(Intercept)	1.647	3.05e-05 ***	1.971	3.81e-06 ***
Zone-lowland	1.613	0.001 ***	1.894	0.0001 ***
Zone-mid-altitude	-2.633	2.05e-06 ***	-2.757	2.34e-07 ***
Zone-riverine	0.642	0.178	0.449	0.299
Season-rainy	7.929	0.023 *	0.45	0.233
log(theta)			-6.725	1.76e-11 ***
ZINB Model: Zero-inflation model coefficients (binomial with logit link):				
(intercept)			**Estimate**	**Pr(>|z|)**
			-1.52	0.298
zonelowland			1.344	0.384
zonemid-altitude			-17.248	0.999
zoneriverine			-11.389	0.984
seasonrainy			-11.708	0.985

Regression models for malaria vectors

The NB model for malaria vectors showed that the lowland and riverine zones, and the rainy season had significant coefficients, and therefore, significantly influenced the distribution of malaria vectors (Table 3). The highland zone and the dry season served as the reference groups. Incident rate ratios for the occurrence of malaria vectors were determined by exponentiating the coefficients obtained from the NB model. The incident rate ratio for the occurrence of malaria vectors in the lowland zone was 144 times more (exp 4.972) than in the highland zone ($p < 0.0001$) and 36 times more (exp 3.588) in the riverine zone compared to the highland zone (p < 0.0001). The effect of seasonality on the occurrence of malaria vectors was not significant.

The coefficients of the binomial part of the ZINB models for both RVF and malaria vectors were all non-significant indicating that the logistic part of the models did not successfully predict the absence of the vectors; the zeroes in the data sets were not due to non-existence of the vectors in the sampling points suggesting that they could have simply been missed in the sampling effort.

Table 3: Regression coefficients for the three regression models performed to test the effect of ecogeographic zones and seasons on the distribution of malaria vectors. The levels of significance are indicated by asterisks where '***' = p-value < 0.0001 and '*' = p-value <0.05.

Coefficients:	NB Model		ZINB Model: Count model coefficients (negbin with log link)	
	Estimate	Pr(>|z|)	Estimate	Pr(>|z|)
(Intercept)	-0.258	0.58	0.476	0.495
zonelowland	4.972	< 2e-16***	4.405	2.85e-07***
zonemid-altitude	0.612	0.297	-0.096	0.908
zoneriverine	3.588	6.01e-11***	2.983	0.0003***
seasonrainy	0.243	0.518	0.164	0.712
Log(theta)			-1.222	1.71e-09***
Zero-inflation model coefficients (binomial with logit link):				
(Intercept)			**Estimate**	**Pr(>|z|)**
			0.670	0.495
zonelowland			-2.386	0.085
zonemid-altitude			-11.298	0.968
zoneriverine			-2.581	0.131
seasonrainy			-1.266	0.327

A comparison of the performance of the NB model (model 1) to the ZINB model (model 2) regression for both RVF and malaria vectors showed that the NB model performed better than the ZINB model (Table 4), the spatiotemporal distribution of the evectors is better explained using the NB model.

Table 4: Vuong Non-Nested Hypothesis Test-Statistic: Test-statistic is asymptotically distributed N(0,1) under the null that the models are indistinguishable.

Vector Category	Vuong Test	z-statistic	Alternate hypothesis	p-value
RVF	Raw	-1.435	model2 > model1	0.076
	BIC-corrected	2.597	model1 > model2	< 0.001
Malaria	Raw	-1.075	Model 2 > Model 1	0.14
	BIC-corrected	6.062	Model 1 > Model 2	< 0.001

For both RVF and malaria models, the raw test shows that the ZINB model does not perform better than the NB model ($p > 0.05$). This conclusion is supported by the BIC-corrected model which shows the NB model performs better than the ZINB model ($p < 0.05$).

Spatiotemporal Risk Maps of RVF and Malaria Vectors

Vectors of the two diseases were more abundant in the rainy season compared to the dry season (G = 499.38, X-squared df = 3, p-value < 0.0001 for RVF and G = 351.27, X-squared df = 3, p-value < 0.0001 for malaria).

The abundance of RVF vectors is shown in figure 4. The highest abundance of RVF vectors during the rainy season was in the lowland zone. During the dry season, there was a shift in the abundance of mosquitoes, the highest count was recorded in the riverine zone and not the lowland zone. The midland zone had the lowest abundance of RVF vectors in both seasons.

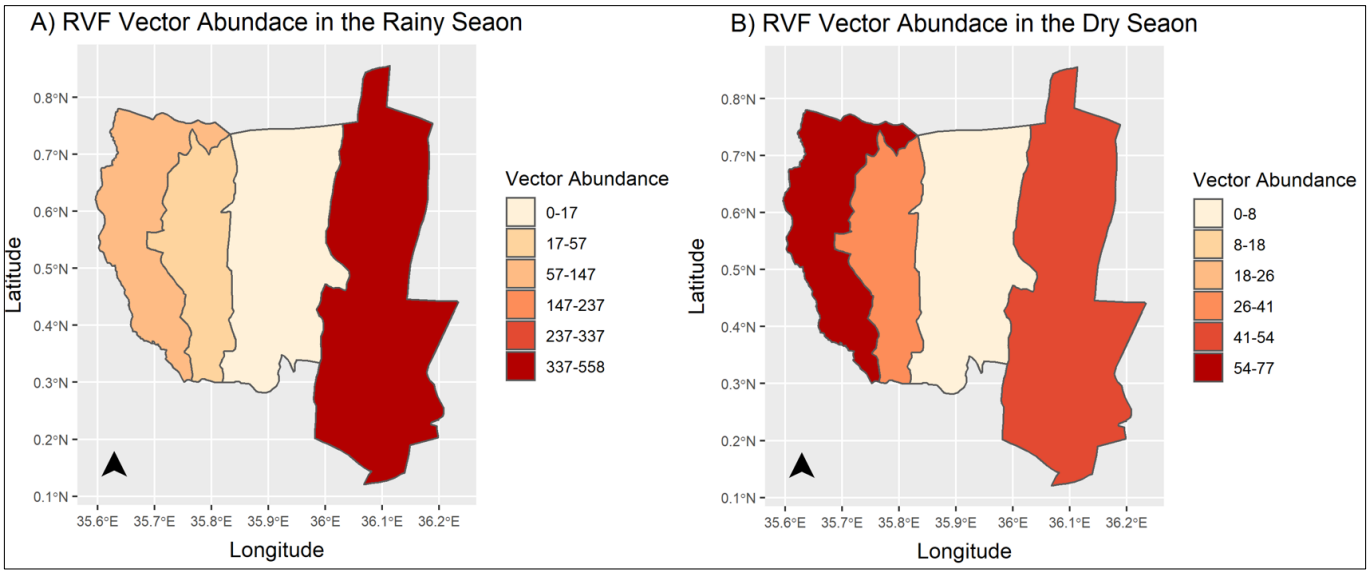

Fig 4: Abundance of RVF vectors across the geographic zones during the rainy and dry seasons. In both seasons, vector abundance is higher the lowland and riverine zones compared to the highland and riverine zones. However, in the dry season, RVF vector abundance is highest in the riverine zone compared to the rainy season. Note: the legends of Figures are not on the same scale, therefore comparisons should not be made between the figures

The abundance of malaria vectors is shown in figure 5. In both seasons, malaria vectors were most abundant in the lowland zone, followed by the riverine zone. The highland and mid-altitude zones had very few mosquitoes (Figure 5).

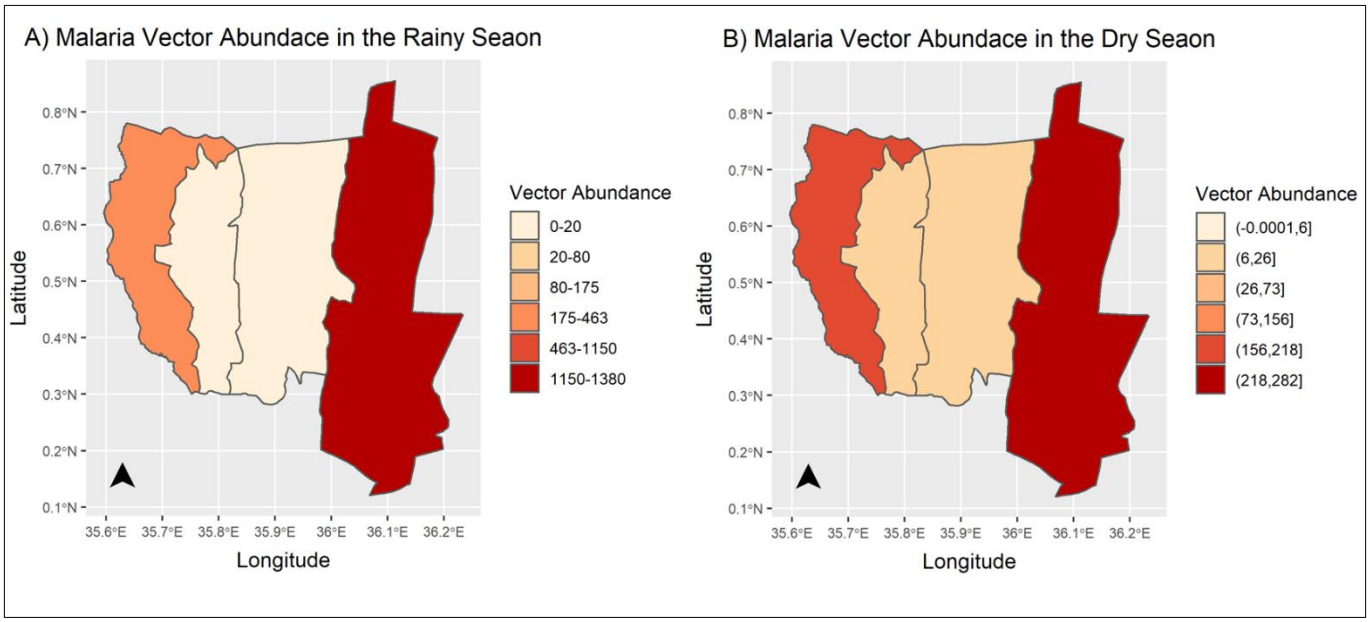

Fig 5: Abundance of malaria vectors across the eco-geographical zones during the rainy and dry seasons. In both seasons, vector abundance is high in the lowland and riverine zones compared to the highland and mid-altitude zone. However, as indicated by the legends, malaria vectors are more abundant during the rainy season compared to the dry season. Note: the legends of Figures are not on the same scale, therefore comparisons should not be made between the figures.

Discussion

Results from the study shows that the abundance of mosquito vectors to the two diseases is climate sensitive, increasing the risk of transmission during the rainy seasons. The study also identifies the lowland and the riverine eco-geographic zones as the possible focal points of RVF and malaria transmission. This is supported by studies during the 2006-2007 RVF outbreaks [5, 6, 2] and investigations into malaria incidence [26, 27]. Intervention strategies on vector control against these two diseases should be focus on the lowland and the riverine ecogeographic zones.

The spatial distribution of RVF and malaria vectors is restricted to the lowland and riverine eco-geographic zones. These two zones possess a blend of climatic, vegetation, and landscape factors that increase the abundance of vectors in the form of permanent water bodies that serve as mosquito breeding sites, dense vegetation and a stable climate seasonality. Previuos studies reported the presence of flood-prone soils with 90% flat topography in the lowland zone as the most influential environmental predictors of RVF vector occurrence in the lowland zone [28], a combination of climatic and vegetation greenness threshold associated with malaria transmission [29] and a positive correlation between malaria vectors abundance and rainfall in some parts of the study area [30].

The temporal distribution of the vectors differed with more mosquitoes being collected in the rainy season compared to the dry season. This finding is supported by other studies that have investigated seasonal trends of mosquito abundance [10, 30, 31]. The rainy season is comprised of the moths of April - May, July - August, and November - December, implying and increased risk of RVF and malaria transmission during these months in the lowland and riverine zones.

Knowledge of the spatiotemporal distribution of RVF and malaria vectors is crucial in implementing vector control as a disease prevention strategy. Vector control interventions can target the lowland and riverine zones that have a high vector abundance of mosquito vectors and it can be timed to coincide with rainy seasons. Indeed, malaria cases in Baringo County have been reported to increase with rainfall with a time lag of 2 months [11]. Malaria prevalence in the study area has been reported as being highest in the riverine zone [26]. Interventions like the supply of long-lasting insecticidal nets, indoor residual spraying and larval source management in the lowland and riverine zones can be timed to coincide with the rainy season. The lowland zone has been the focal point of previous interventions, has received malaria control interventions thereby reducing malaria prevalence. Such interventions should be extended to the riverine zone to reduce the currently high malaria prevelance.

Inter-epidemic RVF surveillance in Baringo County has reported a seroprevalence rate of 5.6% in ruminants [32] and no detection of RVF seroprevalence in human populations [33]. The main RVF intervention strategy has always been the vaccination of animals and quarantines to control movement of animals at the onset of outbreaks [15]. However the cost of the exercise is enormous, and with the functions of the Ministry of Agriculture, Livestock and Fisheries being devolved from the national to the county governments in the new governance structure in Kenya [34], it is a challenge for the county governments to implement.

Current mosquito vector control interventions are used against malaria only. The use of an IVM approach can augment the use of LLINs and IRS against malaria, and it can have the benefit of reducing the abundance of mosquito vectors of other diseases. IVM approaches can be extended to non chemical methods such as house modification to reduce mosquito access through the eaves of houses, use of attractive sugar bait traps, use of mosquito repellants based on indegenious knowledge on plants with mosquito repellent

properties, and changes in sociocultural behaviour that increase malaria risk can greatly reduce malaria transmission.

Since RVF outbreaks occur following the mass emergence of transovarially infected *Aedes* mosquitoes, the best IVM approach should be one that focuses on LSM using eco-friendly larval growth inhibitors and microbial larvicides. Trapping of adult stage mosquitoes using attractive sugar baits can also augment the use of LSM. *Aedes* mosquitoes are known to transmist other arboviruses that cause febrile illnesses, for example, the Semliki Forest virus and Chikungunya virus both of which are present in Baringo County.

Through desigining IVM protocols targeting mosquito vectors of multiple diseases such as used in the "One Health" approach, a single a single IVM effort against a multidisease vector is cost effective. The use of emerging vector control methods like sterile insect technique in mosquitoes and the CRISPR-cas9 gene editing technique in mosquito populations also provide an opportunity that can be employed in the near future to reduce the risk of RVF and malaria transmission.

The success of vector control against transmission of these two diseases should also be guided by evidences from other fields relevant to understanding the epidemiology of the two diseases, for example, climate science, genetic epidemiology, vector biology and medical anthropology. Respectively, contributions from such fields will help in understanding impact of climate change on IVM, track insecticide resistance in vector populations, understand target points in the life cycles of vectors where IVM is most effective and willingness of local populations to take up innovative vector control methods.

Conclusion

This paper presents evidence of spatiotemporal differences in the distribution of RVF and malaria vectors attributable to environmental and climatic variation. These spatiotemporal differences in vector abundance and their correlation to documented disease incidences identify two ecogeographic zones as focal points for RVF and malaria transmission. The findings can therefore be used to design IVM strategies to minimise the transmission of RVF and malaria in the two ecogeographic zones of Baringo County.

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