Dynamic risk model for Rift Valley fever outbreaks in Kenya based on climate and disease outbreak data

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Abstract

Rift Valley fever (RVF) is a mosquito-borne viral zoonotic disease that occurs throughout sub-Saharan Africa, Egypt and the Arabian Peninsula, with heavy impact in affected countries. Outbreaks are episodic and related to climate variability, especially rainfall and flooding. Despite great strides towards better prediction of RVF epidemics, there is still no observed climate data-based warning system with sufficient lead time for appropriate response and mitigation. We present a dynamic risk model based on historical RVF outbreaks and observed meteorological data. The model uses 30-year data on rainfall, temperature, relative humidity, normalised difference vegetation index and sea surface temperature data as predictors. Our research on RVF focused on Garissa, Murang'a and Kwale counties in Kenya using a research design based on a correlational, experimental, and evaluational approach. The weather data were obtained from the Kenya Meteorological Department while the RVF data were acquired from International Livestock Research Institute, and the Department of Veterinary Services. Performance of the model was evaluated by using the first 70% of the data for calibration and the remaining 30% for validation. The assessed components of the model accurately predicted already observed RVF events. The Brier score for each of the models (ranging from 0.007 to 0.022) indicated high skill. The coefficient of determination (R^2) was higher in Garissa (0.66) than in Murang'a (0.21) and Kwale (0.16). The discrepancy was attributed to data distribution differences and varying ecosystems. The model outputs should complement existing early warning systems to detect risk factors that predispose for RVF outbreaks.

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Introduction

Rift Valley fever (RVF) is a viral zoonosis that has had pronounced health and economic impacts in much of sub-Saharan Africa (Anyamba *et al*., 2010). This arbovirus has been responsible for devastating outbreaks of severe human and animal disease, which have gone beyond Africa, reaching the Arabian Peninsula in 2000 (Bird *et al*., 2008). The last major outbreak in East Africa took place 2006-2007 and is reported to have resulted in economic losses exceeding USD 60 million (Anyamba *et al*., 2010). RVF is a vector-borne disease caused by a virus that belongs to the family Bunyaviridae, genus Phlebovirus that affects domestic livestock such as sheep, cattle, camels and goats, in which animal species it causes abortions (Cook and Zumla, 2003) associated with high neonatal mortality (Davies and Martin, 2003). The RVF virus infects also humans (Soti *et al*., 2012). It is transmitted transovarially by *Aedes* or *Culex* mosquitoes (Hightower *et al*., 2012). Since its isolation and characterisation in Kenya in 1931, RVF has been seen to disproportionately affect vulnerable communities with poor resilience to economic and environmental challenge (WHO, 2009; Osman *et al*., 2013).

Major outbreaks were experienced in Egypt in 1977-1978 and 1993, in the Senegal River Valley in 1987, in Madagascar in 1990, 1992 and 2008, in northern Kenya and Somalia in 1997, 1998 and 2007, in Saudi Arabia and Yemen in 2000, in Sudan in 2007 and in Southern Africa in 2010 (Soti *et al*., 2012), often with devastating consequences. For example, the outbreaks in Somali and Ethiopia led to a loss of USD 132 million following Saudi Arabia's imposition of a trade ban on live animals from Ethiopia, Somalia and Kenya (Rich and Wanyoike,

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2010). In Kenya, the spread of RVF has been rising systematically, from the confines of a single district in the Rift Valley area in the 1912-1950 period to 55% of the national districts in 2007. As a result, various parts of the country have gradually become enzootic, resulting in periodic epizootics following the first report of the symptoms connected with this disease in 1912 (Murithi *et al*., 2010). The areas in Kenya where RVF is enzootic include Nakuru, Nairobi, Thika, Maragua, Laikipia, Uasin Gishu, Trans Nzoia, Kiambu, Machakos, Kilifi, and Kwale. Maragua sub-County in Murang'a has had 23 outbreaks since the first report in 1951; Garissa Central sub-County in Garissa has had 21 outbreaks since 1961, when the disease was first reported there, while Kwale in Kwale County has experienced 21 outbreaks since 1961 (Murithi *et al*., 2010).

Early warning messages for RVF outbreaks, especially in East Africa, are often given by international institutions such as the Emergency Prevention System (EMPRES-i), the National Aeronautics and Space Administration (NASA) and the World Health Organization (WHO). In Kenya, Somalia and Tanzania, a RVF model based on satellite measurements of sea surface temperatures (SST) and the normalised difference vegetation index (NDVI) data (a measure of greenness that can vary between -1 and + 1) were used to provide a two to six weeks early warning for December 2006 to May 2007 (Anyamba *et al*., 2009), while other studies have predicted longer lead times. For example, Linthicum *et al*. (1999) showed that the RVF can be predicted 5 months in advance using SST anomalies and satellite NDVI data. The numerous studies and predictions on the risk of RVF outbreaks have mainly been based on satellite data, whereas the current work has used observed climate data from three study sites in Kenya.

The general objective of this study was to develop a dynamic model for predicting the risk of RVF outbreaks in Kenya with a lead-time of at least three months in epizootic areas of the country. The choice of type of model and variables were largely informed by the documented findings of other scientists in an attempt to fill the obvious gaps. Special reference to rainfall, temperature, relative humidity and the normalised difference vegetation index (NDVI).

Materials and Methods

Study sites

The study sites were counties Garissa (0°27'25"S, 39°39'30"E), Murang'a (0°45'S 37°7'E) and Kwale (4°10'S, 39°27E). The specific locations selected were Garissa Central and Bura in Garissa county, Makuyu and Maragua in Murang'a county and Kwale and Kinango in Kwale county as shown in Figure 1. The three sites are at varying altitudes with Garissa at 138 m, Murang'a (Thika) at 1501 m and Kwale 422 m. Meteorological data for Murang'a were obtained from Thika Meteorological Station (0°01'S 37°06E). The three sites were selected because they are key RVF-prone geographical areas of Kenya that are known to have experienced serious RVF outbreaks in the past as they are endemic for the disease (Murithi *et al*., 2010).

All the three counties are in the zone of Kenya that generally experiences two main rainfall seasons, the *long rains* from March to May, and the *short rains* from October to December as shown in Figure 2. The mean maximum and minimum monthly temperature patterns for the study sites are also shown in the figure. As Kwale station does not record temperatures, we used mean monthly temperature data from Moi International Airport (Mombasa), approximately 28 km away from the county headquarters, as proxy data for Kwale.

Primary data

The study sites were drawn from RVF hotspots in Kenya that had experienced at least 21 years of RVF outbreaks since the year of its introduction in the respective sub-counties, and at least 45% of years of involvement in national outbreaks after the RVF introduction. Stratified random sampling was done to obtain two villages per study site, where 50 farmers were then selected for sampling, ensuring that those selected all kept livestock. The sampled respondents provided information, through questionnaires, on their knowledge of the climatic seasons in their geographical areas, the types of livestock kept, and the types of diseases their animals had suffered during the preceding ten years. The information thus obtained was validated by means of interviews with key informants from each of the study sites.

Dynamic risk prediction

A dynamic risk model based on historical RVF outbreaks and climate data to guide veterinary and public health policies on prevention and control of RVF outbreaks was developed from an experimental research design. This is a logistic regression model (within the framework of a generalised linear model) with the RVF cases as response variable where 1 is defined as occurrence and 0 as non-occurrence (Quinn and Keough, 2004). The predictor variables were rainfall, NDVI, relative humidity at 06:00 and at 12:00 GMT, maximum and minimum temperatures and SST. The model was constructed and run by means of the R statistical software (R Core Team, 2014). All predictors were investigated with the aim of a three-month lag period except NDVI, for which a four-month lag period was considered, as it is an indicator for rainfall in the preceding month (Hightower *et al*., 2012). The fitted logistic regression model for each location was the following:

$$\text{glm(formula)} = \text{Cases}\sim\text{factor(Month)} + \text{Rain} + \text{NDVI} + \text{RH06} + \text{RH12} + T_{max} + T_{min} + \text{SSTs}$$

where glm (generalised linear model) is the function designed to fit all the predictors and describes how response variable relates to the linear predictors. Cases indicate occurrences (1) or non-occurrence (0) of RVF; Rain is the measure of the monthly total rainfall in mm; NDVI denotes the mean monthly NDVI figure (between -1 and + 1); RH06 and RH12 are the observed mean monthly relative humidity data (expressed as %) at 06:00 GMT and 12:00 GMT; T_{max} and T_{min} are the mean monthly maximum and minimum temperatures in centigrades; SSTs is sea surface temperature in °C. Month is included in the model as a factor to distinguish it from the predictor variables since it contains repetitive units of 1-12.

Model training and validation

The training model was run on 70% of the weather data and validated on 30% of these data. The training data were from 1981 to 2000, while the validation data were from 2001 to 2010. The RVF prediction models for Garissa, Murang'a (Thika municipality) and Kwale were based on the variables confirmed as significant predictors in the initial run. The adequacy of each of the regression models was checked through an examination of the goodness of fit and determining how similar the observed response variables were to the expected or predicted values (Quinn and Keough, 2004).

Model skill

To evaluate the quality of our models, we used both the summary

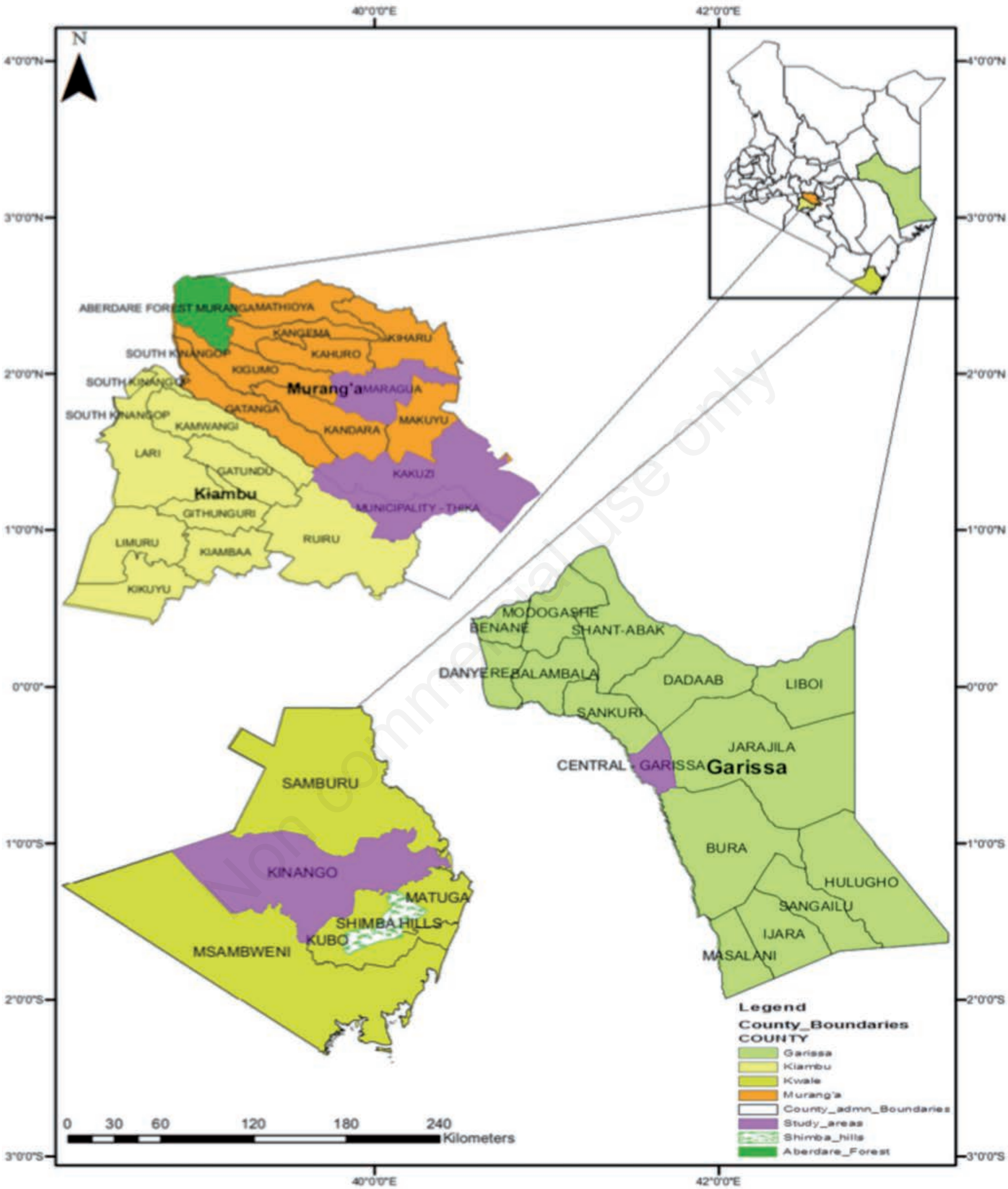

Figure 1. Location of Kenyan Rift Valley fever hotspots exemplified by Garissa, Murang'a and Kwale counties. The figure at top-right is the map of Kenya and the boundaries of its 47 counties. The connecting lines indicate locations of Murang'a, Kiambu, Kwale (bottom left) and Garissa (bottom right) counties. The three counties are a sample of Rift Valley fever hotspots in Kenya. Thika municipality is marked in purple, near Kakuzi, in the top map (Kiambu and Murang'a).

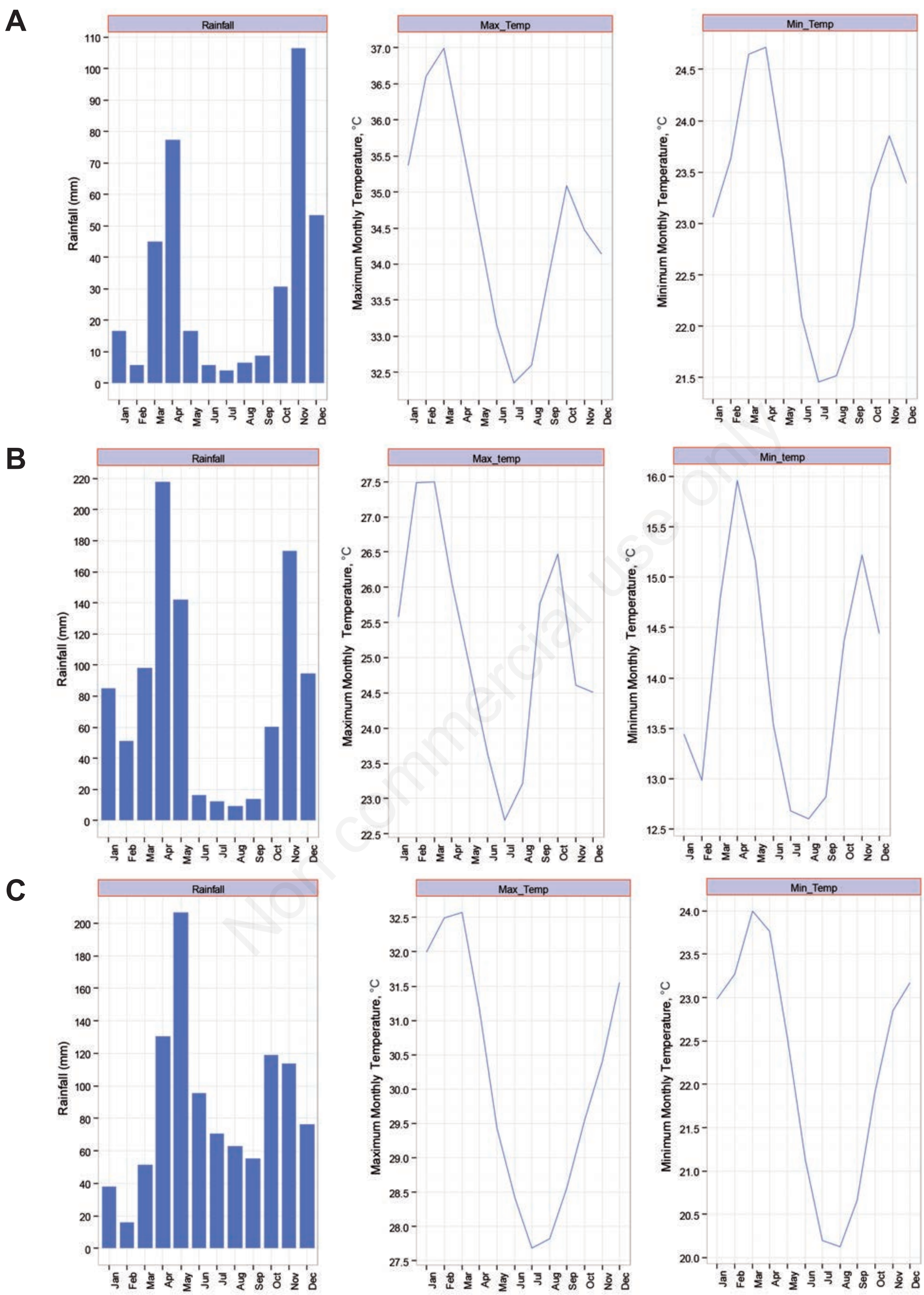

Figure 2. Mean monthly rainfall and temperature patterns: A) Garissa, B) Thika, C) Kwale.

output of the models as well as the coefficient of determination (R^2), which measure the variation in the dependent variable explained by the variation in the independent variable (Keller, 2011) and the Brier Score (BS). The latter is a measure of model errors where BS=0 indicates best skill and BS=1 no skill (Wilks, 2011). This was done by employing the logistic regression function using the R statistical software.

Results

Tables 1-3 show the outputs of the model for Garissa, Thika, and Kwale meteorological stations. They present the estimate, standard error, Z value, P value for the outcome and the variables (rainfall, NDVI, relative humidity, temperatures of air and the sea surface). The variables that the generalised linear model depicted as significant ($P<0.05$) were re-run on the model and the prediction outputs plotted as shown in Figures 3-5. The predictors in the second run were therefore correlated on the basis of their significance in the first run as shown in Tables 1-3. The model for Garissa (Table 1) indicated rainfall, NDVI, RH12, minimum temperature and SST as the stronger predictors ($P<0.05$). Table 2 represents the model output for Thika. It shows the relative humidity at 06:00 GMT and minimum temperature as the only two significant variables in this run of the model. Table 3 depicts the model output for Kwale. It shows that the significant predictors in this zone are relative humidity at 06:00 GMT, minimum temperature and SST. This observation is expected as relative humidity increases with

Table 1. Garissa model output.

Variable (3-month lag)	Estimate	Standard error	Z value	P value	Significance	R^2	Briers score
Rain	-7.279	3.345	-2.176	0.0295	Positive	0.66	0.007
NDVI	-10.285	4.609	-2.232	0.0256	Positive		
RH06	-14.916	8.369	-1.782	0.0747	Negative		
RH12	34.972	17.435	2.006	0.0449	Positive		
T_{max}	22.998	12.457	1.846	0.0649	Negative		
T_{min}	14.587	7.492	1.947	0.0515	Positive		
SSTs	15.270	7.384	2.068	0.0387	Positive		

NDVI, normalised difference vegetation index; RH06, relative humidity at 06:00 GMT; RH12, relative humidity at 12:00 GMT; T_{max}, temperature maximum; T_{min}, temperature minimum; SSTs, sea surface temperatures.

Table 2. Thika model output.

Variable (3-month lag)	Estimate	Standard error	Z value	P value	Significance	R^2	Briers score
Rain	-0.070	0.596	-0.118	0.906	Negative	0.21	0.022
NDVI	1.825	0.674	2.708	0.007	Positive		
RH06	1.294	0.989	1.307	0.191	Negative		
RH12	0.601	1.510	0.398	0.690	Negative		
T_{max}	1.188	1.649	0.720	0.471	Negative		
T_{min}	-2.535	1.280	-2.065	0.039	Positive		
SSTs	84.832	136.108	0.623	0.533	Negative		

NDVI, normalised difference vegetation index; RH06, relative humidity at 06:00 GMT; RH12, relative humidity at 12:00 GMT; T_{max}, temperature maximum; T_{min}, temperature minimum; SSTs, sea surface temperatures.

Table 3. Kwale model output.

Variable (3-month lag)	Estimate	Standard error	Z value	P value	Significance	R^2	Briers score
Rain	0.363	0.832	0.436	0.663	Negative	0.16	0.018
NDVI	-742.813	416.474	-1.784	0.075	Negative		
RH06	-55.101	21.067	-2.615	0.009	Positive		
RH12	31.865	18.440	1.728	0.084	Negative		
T_{max}	17.743	93.146	0.190	0.849	Negative		
T_{min}	-137.579	61.699	-2.230	0.026	Positive		
SSTs	364.209	153.384	2.374	0.018	Positive		

NDVI, normalised difference vegetation index; RH06, relative humidity at 06:00 GMT; RH12, relative humidity at 12:00 GMT; T_{max}, temperature maximum; T_{min}, temperature minimum; SSTs, sea surface temperatures.

decrease in temperature reaching its highest value very early in the morning under conditions of an unchanging dew point temperature.

It is also noteworthy that the minimum temperature variable was found to be significant in all the respective runs of the model in Garissa, Murang'a and Kwale. NDVI seemed to be a stronger predictor than rainfall, as it is a measure of greenness recorded every month compared to dry periods that at times record no rainfall in a month. The SST variable was depicted as a significant predictor for Garissa and Kwale but not for Murang'a, a fact that could be attributed to the proximity of the two sites to the Indian Ocean. Proximity to the sea puts Garissa and Kwale within the same surface wind regimes. An earlier study by Indeje and Semazzi (1999) confirms the existence of a strong correlation between rainfall over parts of East Africa and the lower equatorial stratospheric zonal wind during the months of March-May and June-August. Wolff *et al*. (2011) observe the broad inverse relation between rainfall and windiness in their description of the characteristic surface ocean warming in the western Indian Ocean that leads to intensification and shifts of the Inter-Tropical Convergence Zone (ITCZ), resulting in increased precipitation over East Africa and weakening of the local surface winds.

Rift Valley fever prediction for Garissa county

Figure 3 (A) is the training model output, while Figure 3 (B) is the validation model output for Garissa county. Figure 3 (A) shows that the model accurately predicts the outbreaks of Rift Valley fever in 1997 and 1998 and Figure 3 (B) that the validation model predicts the outbreak as observed at the end of 2006 and beginning of 2007. These outputs were based on rainfall, NDVI, relative humidity at 12:00 GMT, minimum temperature and SST, the variables found to be significant predictors in the initial run of the model aimed to determine the strength of the meteorological predictors (Table 1).

The outcome suggests that the selected parameters are part of the variables that may be related to the development of meteorological systems that are conducive to the development of the RVF vectors as well as the virus that causes the RVF. As a measure of vegetation, NDVI is related to rainfall, which is especially evident in rain-fed natural ecosystems and agricultural areas (Anyamba *et al*., 2010). Warm minimum temperatures facilitate the development of mosquito larvae in flooded waters following heavy rainfall episodes. This argument is supported by the temperature patterns that characterise the Garissa area.

Rift Valley fever prediction for Murang'a county

Figure 4 presents the RVF prediction for Murang'a county. The prediction model was trained using weather data from 1981 to 2000 resulting in the output as shown in Figure 4A. The significant parameters in the initial run of the model were NDVI and minimum temperature (Table 2). The model was validated by means of weather data from 2001 to 2010 resulting in the output as shown in Figure 4B. The outcomes of both models depict accurate prediction, as the Department of Veterinary Services (DVS) reports confirm that there were RVF outbreaks in 1983, 1989, 1993, 1997 and 1998 as indicated in Figure 4A and in 2006-07 as shown in Figure 4B. The topography of Murang'a county, at an average altitude of 1200 m, shares the proximity of the central highlands, where greenness may be assumed even during long periods of absence of rain. NDVI may therefore be a stronger predictor than rainfall, though it may not ensure availability of vector habitats without water. Elevated minimum temperatures during the peak months of the rainfall seasons are conducive to mosquito larval development and may therefore be a factor that enhances the predictive aspect of the parameter.

Rift Valley fever prediction for Kwale county

The outputs of the prediction and validation models for RVF in Kwale county are shown in Figure 5A and B, respectively. This output is based on relative humidity at 06:00 GMT, minimum temperature and SST, the

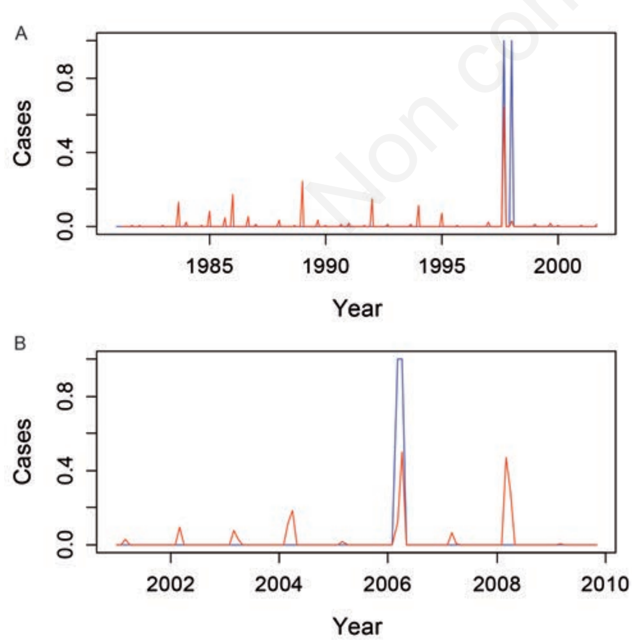

Figure 3. Rift Valley fever prediction in Garissa: model outputs. A) training, B) validation. The red lines are for predicted outbreaks while the blue ones represent actual occurrences.

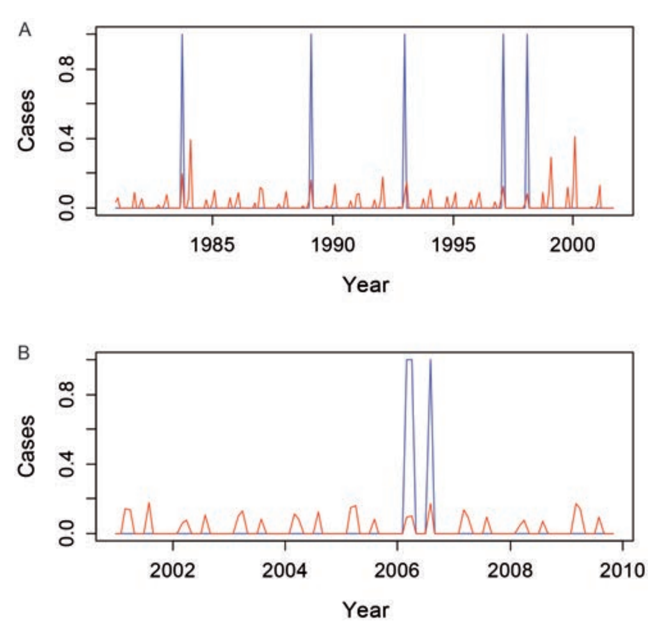

Figure 4. Rift Valley fever prediction in Murang'a: model outputs. A) training, B) validation. The red lines are for predicted outbreaks while the blue ones represent actual occurrences.

variables that were found to be significant predictors in the initial run of the model that was aimed to determine the strength of the meteorological predictors (Table 3). The training model accurately predicted the RVF outbreaks of 1983, 1993 and 1998. Although it gives very weak signals for 1989 and 1997, when RVF outbreaks also occurred according to the DVS records, the validation model was found to predict the 2006 RVF outbreak fairly accurately (Figure 5B).

Discussion

Bearing in mind the need for massive applications of control measures at the earliest indications of elevated rainfall and flooding, it was felt to be important to consider the accuracy of the data used in modelling, given the huge costs involved in administering sustained mosquito larval control.

General performance of the model

Varying coefficients of determination were obtained. Garissa had R^2=0.66, Murang'a R^2=0.21 and Kwale R^2=0.16. While the topographical differences between the three sites may be appreciated, the low coefficients of determination for Murang'a and Kwale suggest the need for further refinement of the model. In order to improve on the skill of the model, the climatological patterns should be considered with regard to the difference in dates of onset of the rainfall seasons by the geographical and ecological zones. Further research on season-based patterns of discreet weather variables with respect to RVF outbreaks could yield important results. With respect to risk mapping, thresholds could also vary with geographical location, while some may flood upon receiving seasonal rainfall in excess of 400 mm, others may do so already at 200 mm in a season (Anyamba, 2010). These could at least explain part of the variation in model output.

The training and validation models also show peaks when the weather conditions could have favoured RVF outbreaks. Absence of outbreaks where such peaks do not coincide with observed or reported outbreaks could be attributed to acquired immunity.

It was noted that besides the positive predictions that were confirmed by reports of actual outbreaks, especially the 1983, 1989, 1993, 1997-98 and 2006-07 RVF outbreaks, the model output included positive predictions where there were no outbreaks. Even though we could not explain all the *false positives*, we found that most of them coincided with periods of extreme rainfall events. Some of the notable years in this respect are 1987-88, 1991-92 and 2000-01 as shown in Figure 6A-C, which present the rainfall anomalies time series from 1981 to 2010 at Garissa, Thika and Kwale, respectively. In our view, the model predicts risk during these periods based on the favourable factors, rainfall being a key variable. It may also be pointed out that interventions, following regular surveillance by the DVS, may have provided immunity to livestock, thereby reducing the risk of a RVF outbreak in spite of mete-

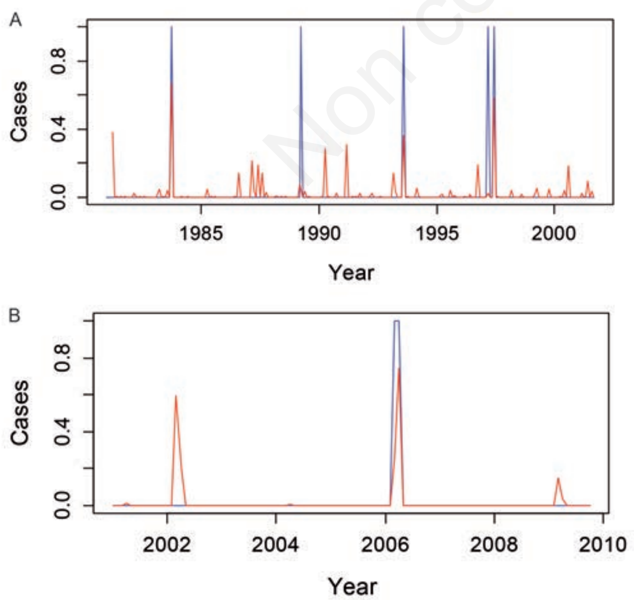

Figure 5. Rift Valley fever prediction in Kwale: model outputs. A) training, B) validation. The red lines are for predicted outbreaks while the blue ones represent actual occurrences.

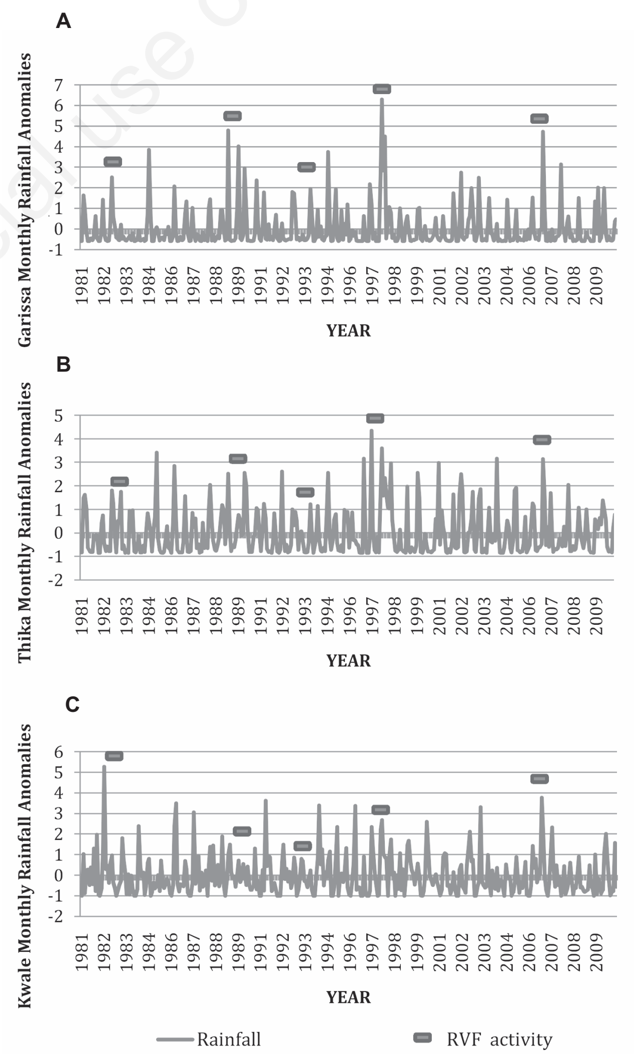

Figure 6. A time series plot of rainfall anomalies and Rift Valley fever prediction epidemics in the period January 1981 to December 2010. A) Garissa, B) Thika, C) Kwale.

orological factors favourable for infection indicated by the model. Besides the acquired immunity suggested here, there may also be undetected, yet significant, demographic and spatial expansion of the RVF virus during the intervening period between one and two outbreaks (Bird *et al*., 2008).

Variables of importance

Variables thought to have an influence on the epizootic include the Southern Oscillation Index (SOI) (http://www.cgd.ucar.edu/cas/catalog/climind/soi.html) and the SST. The SOI has been considered in the effort to determine the best predictors of RVF by means of autoregressive integrated moving average (ARIMA) models (http://people.duke.edu/~rnau/411arim.htm). Past RVF events in East Africa have been found to be closely linked to the occurrence of the warm phase of the El Niño Southern Oscillation (ENSO) (http://climate.ncsu.edu/climate/patterns/ENSO.html), a phenomenon that is accompanied by prolonged periods of warm SSTs in the central, eastern equatorial Pacific Ocean and the Indian Ocean (Kelly-Hope and Thomson, 2008). These conditions lead to heavy rainfall and flooding of vast areas that serve as habitats for *Culex* and *Aedes* mosquitoes, the primary vectors of the RVF virus (Anyamba *et al*., 2010). It is on this basis that the SST as a variable was included as a factor in the models.

Anyamba *et al*. (2010) used NDVI as proxy for ecological dynamics and rainfall. This requires a lag of about one month as NDVI is a measure of vegetation greenness, which in turn is closely related to rainfall. In an attempt to develop a model for the prediction of RVF in the East African region with a lead time of 2 to 5 months, Linthicum *et al*. (1999) used equatorial Pacific and Indian Ocean SST as well as NDVI anomaly data. We used lagged NDVI data by one month as input in the model for comparison purposes, since this study was largely based on observed actual meteorological data. As proxy for rainfall, it may, however, be misleading if applied to areas that rely on irrigation or where there have been sudden or recent changes of land use.

While NDVI and SST components are commonly referred to, both in this study and the one by Linthicum *et al*. (1999), satellite-generated data on weather variables such as rainfall, relative humidity and temperature must also be taken into account. Most RVF outbreaks in Kenya are associated with above-normal rainfall, which is mainly responsible for favouring breeding of the vector mosquitoes by creating conditions allowing sufficient amounts of surface water. The fact that mosquito eggs can only hatch in water enhances the recognition of rainfall as one of the major factors influencing the transmission of RVF. In arid and semi arid zones, such as Garissa, where the average monthly rainfall does not exceed 120 mm (Figure 2A), rainfall curtails RVF transmission. It is thus an important component in the model owing to its impact on the vectorial capacity of RVF.

Temperature is recognised as another key variable that also influences the vectorial capacity through its dual effect on the vector mosquito and the growth of the RVF parasite in its body. Temperature variations influence the extrinsic incubation period (EIP) of the virus, effects that not only vary with the mosquito species but also the virus genotype (Reisen *et al*., 2006). Temperature affects also the development rates of mosquito larvae, the gonotrophic cycle as well as the survivorship of both the adults and the larvae (Ceccato *et al*., 2012). In Kwale county (coast) and Garissa [arid and semi arid lands (ASAL)], temperature is not the limiting factor for the development of the vector, as average temperatures rarely go below 18°C, as it is in Murang'a, where marked seasonal variations are observed. The three models presented portray minimum temperature as an important variable, while maximum temperature is downplayed rendering credence to the minimum temperature variable as an important factor in the development of mosquito larvae. Figure 2A-C shows that April, the peak month of the Long Rains season, is also the month with the highest average mean minimum temperature, a situation that clearly favours the development of mosquito larvae (Muturi *et al*., 2007).

Relative humidity was considered as an important component by us as different *Culex* species have been found generally not to live long enough to complete their transmission cycle when the relative humidity is consistently below 60% (Grover-Kopec *et al*., 2006; Muturi *et al*., 2007). Relative humidity is therefore an important predictor alongside temperature and rainfall. Common *Culex* habitats are ponds, bamboo, fallen logs, leaf axils, streams and rock pools (Muturi *et al*., 2007). One of the features observable in these habitats is their high capacity for holding water as well as retention of humidity. Relative humidity is a limiting factor in Garissa as the monthly average never goes beyond 62% even in April and November, which are the wettest months. It is notable that the model picks relative humidity at 12:00 GMT as a significant predictor for Garissa and RH at 06:00 GMT for Kwale county given that it is a limiting factor in Garissa (ASAL) but not in Kwale (coast).

The presence of RVF may have been sustained and often amplified by the ease of movement of animals within different ecological zones. The Kenyan coast, where Kwale county is located, is listed among zones considered to be outside the potential epizootic area mask with regard to the 2006-07 RVF epidemic (Anyamba *et al*., 2010). This observation was corroborated by respondents and key informants during interviews conducted for this study.

Conclusions

A dynamic high-skill model for the prediction of RVF outbreaks in three specific Kenyan counties was developed and validated. The model outcomes varied with geographical location and meteorological variables, such as rainfall, NDVI, temperature, relative humidity and SST at a lead-time of three months. The differences were also attributed to data distribution differences as well as the varying ecosystems represented by the three sites. Besides rainfall, minimum temperature was found to be the most significant predictor in each of the models. The results suggest the need for consideration of strategic uses of the dynamic risk prediction models with respect to geographical zoning and other meteorological predictors. The installation of automatic weather stations, especially in areas without meteorological stations, would improve the accuracy of the risk prediction considerably. Strategic uses of this model approach include timing of mitigation programmes such as vaccination, guided by the dynamic prediction model. Awareness programmes on the predictive signals from the model would also go a long way towards reaching livestock herders and farmers.

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