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Climate change and the tick-borne disease, *Theileriosis* (East Coast fever) in sub-Saharan Africa

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Abstract

The impacts of climate change on the range of the tick-borne disease *Theileriosis* (East Coast fever (ECF)) in sub-Saharan Africa are predicted using a species distribution model and current and future climates simulated by the nested regional climate model DARLAM (Division of Atmospheric Limited Area Model). These results, based on the predicted distribution of the main tick vector species (*Rhipicephalus appendiculatus*) and its host, cattle, shows that the Northern Cape and Eastern Cape provinces of South Africa, Botswana, Malawi, Zambia and eastern DRC show increases in ECF suitability. Other areas in sub-Saharan Africa show different rates of range alteration. These range alterations are in response to the predicted general change in mean minimum, maximum temperature and rainfall in the months of January and July. The ECF sub-Saharan risk map provided is a necessary tool to complement existing traditional control methods. Understanding and mapping changes in space and time of this disease are a prerequisite to sustainable disease reduction since it is then possible for current and future disease control programs to be timely and directed at specific areas based on risk maps.

Keywords: DARLAM; Epidemiology; Predictive species modelling; *Rhipicephalus appendiculatus*; Vector-borne diseases

1. Introduction

East Coast fever (ECF), caused by a protozoan parasite *Theileria parva*, is one of the most important livestock diseases in Africa (Lessard et al., 1988; Muraguri et al., 1999). It depends on the tick *Rhipicephalus appendiculatus* Neuman 1901, a three-host tick, which parasitises mainly cattle, for its transmission and its distribution is directly related to the distribution of the tick. The distribution range of ECF extends south from southern Sudan to eastern South Africa and as far west as the Democratic Republic of Congo (DRC). ECF

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kills 1.1 million cattle and causes an economic loss of $168 million annually (Norval et al., 1992). Mortality is higher (up to 100%) in the more expensive exotic cattle than in the indigenous Zebus, where the average mortality is estimated at 10% and if uncontrolled, ECF can cause over 90% mortality of susceptible cattle following its introduction into a region (Lawrence et al., 1988).

Apart from direct losses due to cattle mortality, in endemic areas where chronic ECF occurs, other less quantifiable effects of the disease are apparent including poor weight gain, low fertility rates, reduced growth and milk production, paralysis, and secondary attacks from other parasites (Pegram et al., 1989). ECF is therefore a major reason for tick control in most African countries. A main form of control, the use of acaricide, is, however, complicated by its high cost, development of tick resistance (Cox, 1991), stock movement during drought, inefficient supervision of ECF quarantines, abundant tick-carrying wildlife, insufficient knowledge of tick ecology and lack of adequate dipping facilities; not to mention concerns about the potential environmental consequences of this control program (Cox, 1991). Moreover chemical control has proved unsuccessful partly because partial removal of one parasite results in invasion of others. For instance, removal of *Glossina palpalis* in Cote d'Ivoire resulted in invasion of lesser dominant species, *Glossina pallicera* and *Glossina nigrofusca*. Also the eradication of *Boophilus decoloratus* in southeastern countries resulted in the invasion of its competitor, *B. microplus* (Sutherst, 2001).

Furthermore, *R. appendiculatus* is a generalist parasite, although cattle are the preferred domestic hosts of all stages of its development (Norval and Lightfoot, 1982; Okello-Onen et al., 1999). Such generalist parasites like *R. appendiculatus* represent a group of special concern in the context of invasive species and climate change (Cumming and van Vuuren, 2006). Generalist parasites could have a variety of direct and indirect impacts on ecosystems that they invade and a potential to alter disease transmission cycles, opening up new realms to emerging diseases. Prior knowledge of ECF risk areas before any chemical control is considered would improve its application. The aim of this paper is to prepare ECF risk maps in sub-Saharan Africa based on current and future modelled distributions of *R. appendiculatus* and their cattle hosts.

2. Materials and method

This study covers sub-Saharan Africa which was divided into 3000 grids cells of 60×60 km resolution as determined by DARLAM climate data (Engelbrecht et al., 2002). Each of the 3000 grid cells was populated with 6 climate variables and a presence or absence record of the tick *R. appendiculatus* (Cumming, 1999). A detailed description of this method is available in Olwoch et al. (2003). Cattle density data including both indigenous and exotic breeds were added in ArcView GIS (ESRI, Redlands, California) through spatial interpolation. The original cattle data were obtained from Kruska et al. (1995).

2.1. Predicting the current and future distribution of R. appendiculatus and ECF

A predictive species model from Erasmus et al. (2002) was used to predict the current and future distribution of the tick species. The specific methodology used in this study can be obtained from Olwoch et al. (2003). These distributions were refined through the use of cattle distribution data in order to predict the potential current and future distribution of ECF. The predictive modelling was executed in S-Plus (S-Plus 2000) while maps of the results were drawn in ArcView GIS (ESRI, Redlands, California). The resultant potential distributions are maps of probability of occurrences per 60 km $\times$ 60 km grid cell based on climate and cattle data.

2.2. Comparison of the predicted present and future distribution of R. appendiculatus and ECF

Several analyses were performed to compare the predicted current and future distributions of both *R. appendiculatus* and ECF. These included: (i) an analysis of range contraction, expansion and shift; (ii) an assessment of the degree of proportional overlap between current and future distributions; and (iii) a comparison of the probability of occurrence values per grid cell between current and future predictions. These analyses were done for the entire study area, per region and per country. The regions are: Southern Africa which includes South Africa, Botswana, Zimbabwe, Zambia, Malawi, Angola and Mozambique; Central

Africa which includes DRC, Rwanda and Burundi; and East Africa which includes Uganda, Kenya and Tanzania.

In the analysis of range alterations, the predicted current or future distribution was taken as the number of grid cells where the probability of occurrence is equal to or greater than 50% for *R. appendiculatus*. The predicted current and future distribution of ECF were taken as the grid cells having a probability of *R. appendiculatus* equal or greater that 50% and a presence of cattle. The difference in grid cells between the predicted current distribution (CD) and predicted future distribution (FD) of the tick and the disease constitutes distribution range change (DC). These range changes may either be range contraction or range expansion. There is a range expansion if FD > CD and there is a range contraction if FD < CD. Maps of range shifts were obtained by overlaying the number of grid cells with probability values >50% before climate change with the number of grid cells with probability values >50% after climate change. The number of grid cells outside the intersection constitutes range shifts in a specified direction.

The degree of proportional overlap between the predicted current and future distributions of *R. appendiculatus* and ECF was assessed by means of proportional overlap method (Prendergast et al., 1993; Reyers et al., 2000). In this case the proportional overlap was calculated as Nc/Ns, where Nc is the number of common grid cells between a pair of areas under comparison and Ns is the number of grid cells in the smallest set of areas containing data for both groups or the number of grid cells in the smallest set minus the number of grids that are not common in these two sets. Finally, a comparison was made between the number of grid cells in various probability classes in the current and future predictions. These probability classes used here are: 0–<20%, 20–<40%, 40–<60%… 80–100%.

3. Results

3.1. DARLAM's climatological anomalies

The climatological anomalies for the 2020s vs. the 1990s as predicted by DARLAM are shown in Fig. 1. January minimum and maximum temperatures are simulated to increase by more than 2 °C over certain regions of the subcontinent. Much of the eastern regions are expected to become drier with an associated pattern of higher sea-level pressure, whilst the western subcontinent is expected to become wetter. An interesting feature of the July anomaly fields is that parts of the central subcontinent are simulated to become cooler and wetter.

3.2. Current and future *R. appendiculatus* predicted distribution

Analysis of range alteration showed varying results. On a sub-Saharan scale, the analysis showed a general reduction of 23.3% in *R. appendiculatus* range between predicted present (CD = 1263 grid cells) and predicted future (FD = 969 grid cells). Regional analysis revealed less than 1% decrease of *R. appendiculatus* range across all regions (Table 1). Range shift was mainly from west to east with most of the range reduction taking place in the west (Figs. 2 and 4). The country analysis showed that Botswana, Malawi, South Africa and Zimbabwe are predicted to show increases while Mozambique, Tanzania, Uganda, Kenya, DRC and Zambia show slight decreases. The countries that are predicted to show no change are Burundi, Rwanda (Table 2).

Analysis of the spatial congruence between predicted current and future *R. appendiculatus* ranges by means of the proportional overlap method showed high congruency between current and future predicted distributions. On a sub-Saharan scale there was 89% congruence between current and future predicted distribution of *R. appendiculatus* (Table 1). On a regional scale, there is a 90% congruence in Central and East with 87% congruence in the South (Table 1). Country proportional overlaps vary from 77% for Botswana, 78% for South Africa, 85% for Zimbabwe and 87% for DRC. The rest show 90% overlaps apart from Rwanda, Burundi and Malawi that show 100% congruency (Table 2).

Analysis of the number of grid cells falling into different probability classes for the whole of sub-Saharan Africa (Table 3) shows increase in the number of grid cell in the 0–20% and 40–60% probability classes. Also of interest was the reduction in the number of grid cells with a probability greater than 80% for the predicted future distribution. Differences in the number of grid cells predicted per probability class at a regional scale for

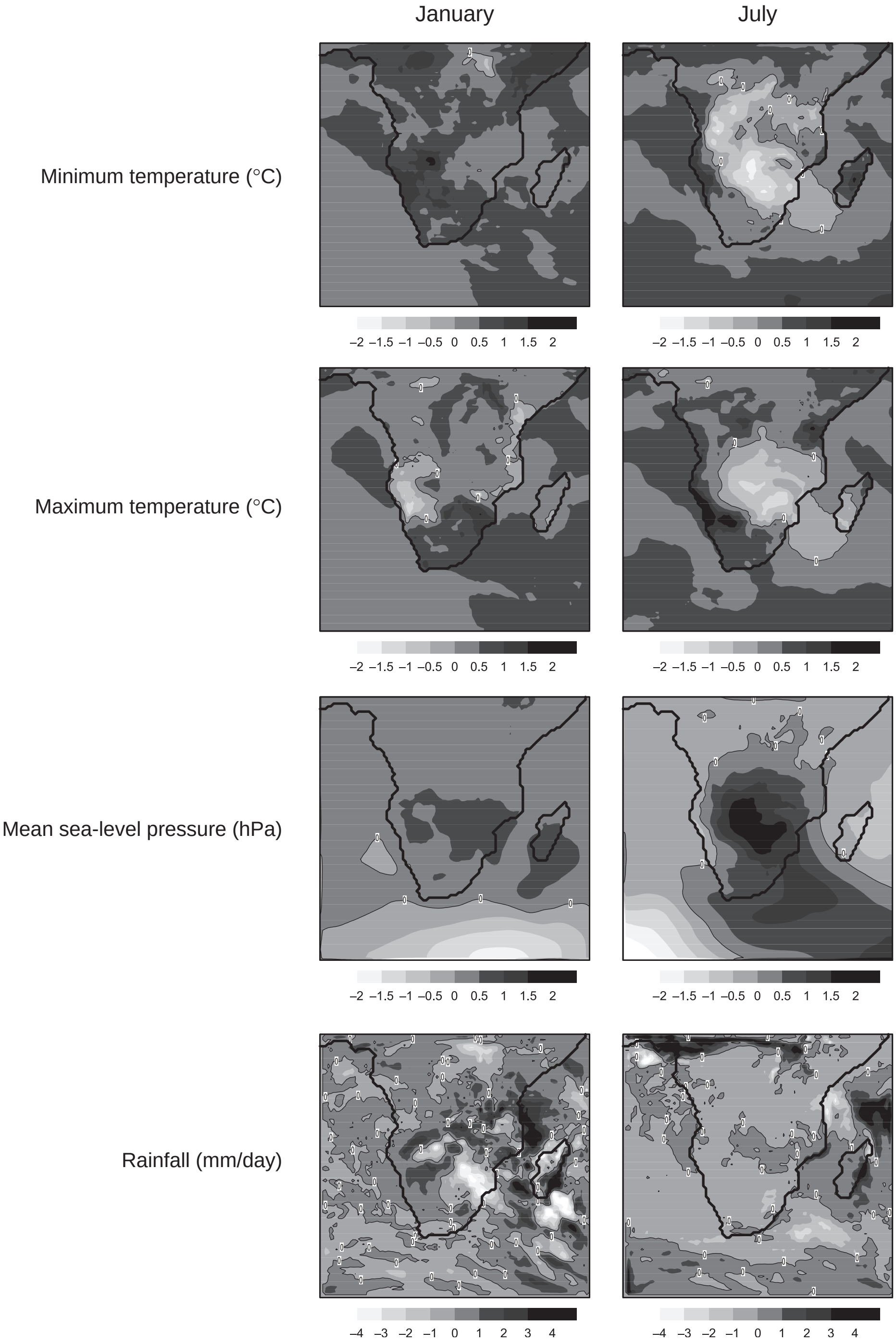

Fig. 1. DARLAM's climatological anomalies for the 2020s vs. 1990s.

R. appendiculatus distribution revealed that the East Africa is predicted to be the most affected region. There is greater than 100% increase in the number of grid cells in the 60–80% probability class. A further analysis of probability classes for individual countries revealed that in most of the countries tick suitability would stay the same. However, the following exceptions were noted: Burundi, Kenya, Rwanda, Zambia, Zimbabwe and Uganda showed significant increases in the number of grid cells with higher probabilities (60–80%)

Table 1
Number of 60 km × 60 km grids cells for which *R. appendiculatus* is present in the predicted current and future distribution at a sub-Saharan and regional scale

Region	Current no. of predicted presence grid cells	Future no. of predicted presence grid cells	No. of overlapping grid cells	Proportional overlap (%)
Sub-Sahara	1233	969	867	89
Central	437	403	373	93
East	254	234	213	91
South	572	563	490	87

Proportional overlap values between current and future ranges are also shown. Presence assumed at a threshold of 50%.

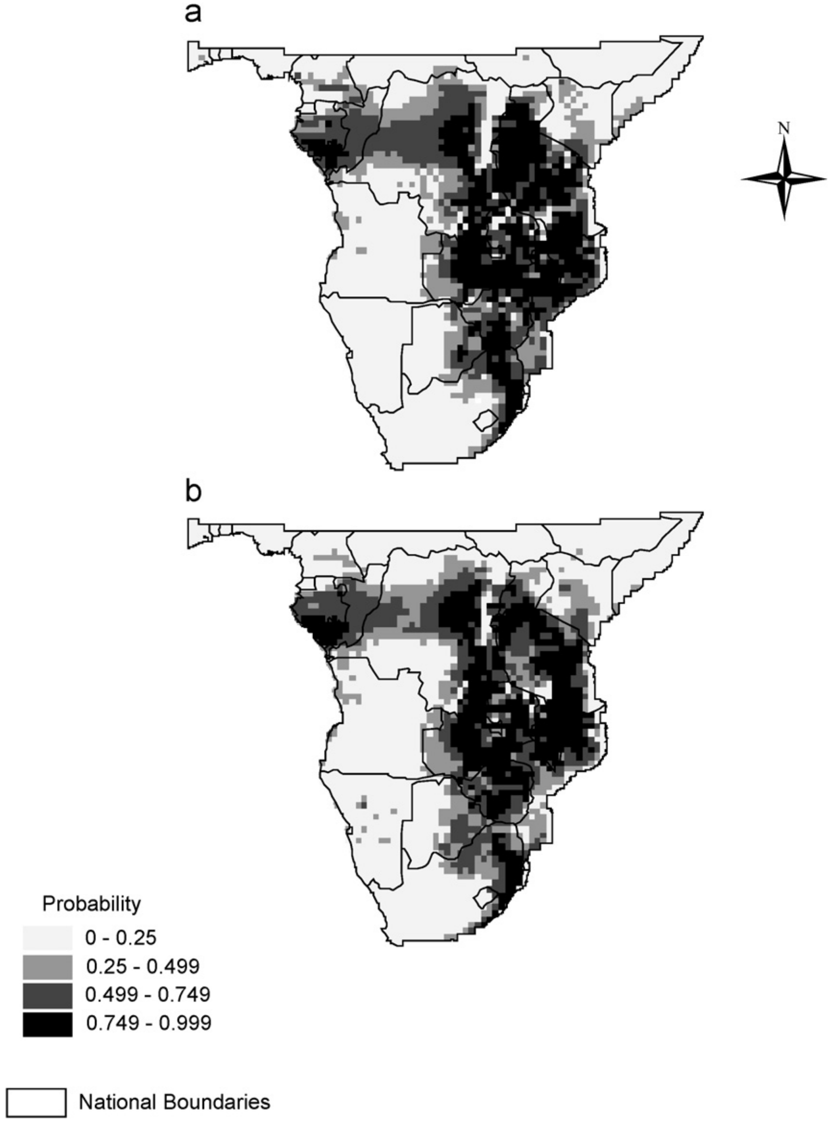

Fig. 2. The current and future predicted probability of occurrence values of *R. appendiculatus* obtained by using the predictive species model (Erasmus et al., 2002) and DARLAM climate surfaces: (a) current, (b) future 2030.

Table 2
Number of 60 km × 60 km grids cells for which *R. appendiculatus* is present in the predicted current and future distribution at a country scale

Country	Current no. of predicted presence grid cells	Future no. of predicted presence grid cells	No. of overlapping grid cells	Proportional overlap (%)
Botswana	39	44	34	74
Burundi	13	13	13	100
Kenya	21	20	14	93
Malawi	35	38	35	100
Mozambique	156	119	114	93
South Africa	86	78	61	78
Rwanda	12	12	12	100
Tanzania	191	182	168	93
Uganda	42	32	31	91
Zaire	283	250	231	87
Zambia	157	155	148	95
Zimbabwe	91	100	83	85

Proportional overlap values between current and future ranges are also shown. Presence assumed at a threshold of 50%.

Table 3
Number of 60 km × 60 km grid cells falling into various probability classes for the presence of *R. appendiculatus* under the predicted current and future distribution at sub-Saharan scale

Probability class (%)	Current no. of predicted presence grid cells	Future no. of predicted presence grid cells	No. of overlapping grids cells	Proportional overlap (%)
0–20	1428	1486	1341	94
20–40	376	357	166	46
40–60	369	383	165	45
60–80	372	369	178	48
80–100	455	405	321	79

The number of grid cells which remain constant in terms of the probability class are also demonstrated as is the proportional overlap.

(Fig. 3a, 3b) while DRC showed increases in the number of grids in the 20–40% probability classes in the future (see also Fig. 4).

3.3. Current and future ECF predicted distribution

On a sub-Saharan scale there was a slight increase in ECF range between present and future (Table 4). The difference between the maps (Fig. 5) of ECF predicted range under the current climatic conditions and future climate showed that 204 grid cells which were suitable for ECF under the current climatic conditions become unsuitable in the future while 103 grid cells which were unsuitable in the current climate become suitable in the future. Visually, most of the southwestern African countries of Angola, Namibia, western and southern Botswana, western Zambia and central DRC are predicted to become unsuitable for ECF in the future. Regionally, there is a predicted increase of ECF in Southern and Central Africa while East Africa stays the same (Table 4). An analysis of individual country ECF changes revealed that the range is predicted to increase in Botswana, DRC, Malawi, and South Africa. Predicted decrease in ECF is expected in Tanzania and Uganda (Table 5). ECF in the rest of the countries (Burundi, Kenya, Mozambique, Zambia and Zimbabwe) stays the same. Analysis of the predicted ECF ranges for the present and future using proportional overlap method showed the lowest congruency in Kenya, followed by Botswana and South Africa (Table 5).

4. Discussion

The predicted reduction in *R. appendiculatus* range particularly in the western arid regions of Africa is in response to predicted increases in temperature in an already hot and dry area limiting population increase, and any further rise in temperature may result in slowing down developmental rates and later limit or halt survival due to water loss under dry conditions. Angola, Namibia, southern DRC become climatically unsuitable for *R. appendiculatus* infestation. However, the northern and eastern Cape provinces of South Africa as well as Botswana, Zambia and eastern DRC, that are currently unsuitable, are rendered climatically suitable for *R. appendiculatus* under future climate scenarios. This may be because of enhanced rainfall in these areas. Rises in temperature (especially the minima) as predicted over most of tropical Africa and southern Africa may contribute to the increases in suitability of *R. appendiculatus* in these regions. These effects would shorten generation time and may allow populations to pass through additional generations, possibly leading to higher tick populations in some cases.

Increase in tick numbers, as well as shifts in the timing and duration of each generation time may overwhelm areas that may become more suitable for tick infestations. This would increase the absolute amount of production loss of cattle. Thus strategic dipping may not be a sufficient strategy in such an environment. The predicted general increase in minimum temperature in most areas, which is the main determining factor in the increase in tick distribution, as well as an increase in the ticks generation time means that there is a higher chance of ticks coming into contact with hosts. This scenario is, in particular, applicable to southern Africa, which currently experiences only one generation of *R. appendiculatus* per year compared to the tropical African countries.

Change in grid cells per probability class shows the importance of analysis of climate impacts on smaller local scales implying that knowledge of the overall change in size of the range is not enough; rather local assessments are necessary to capture these local variations. It can be deduced from this result that although in

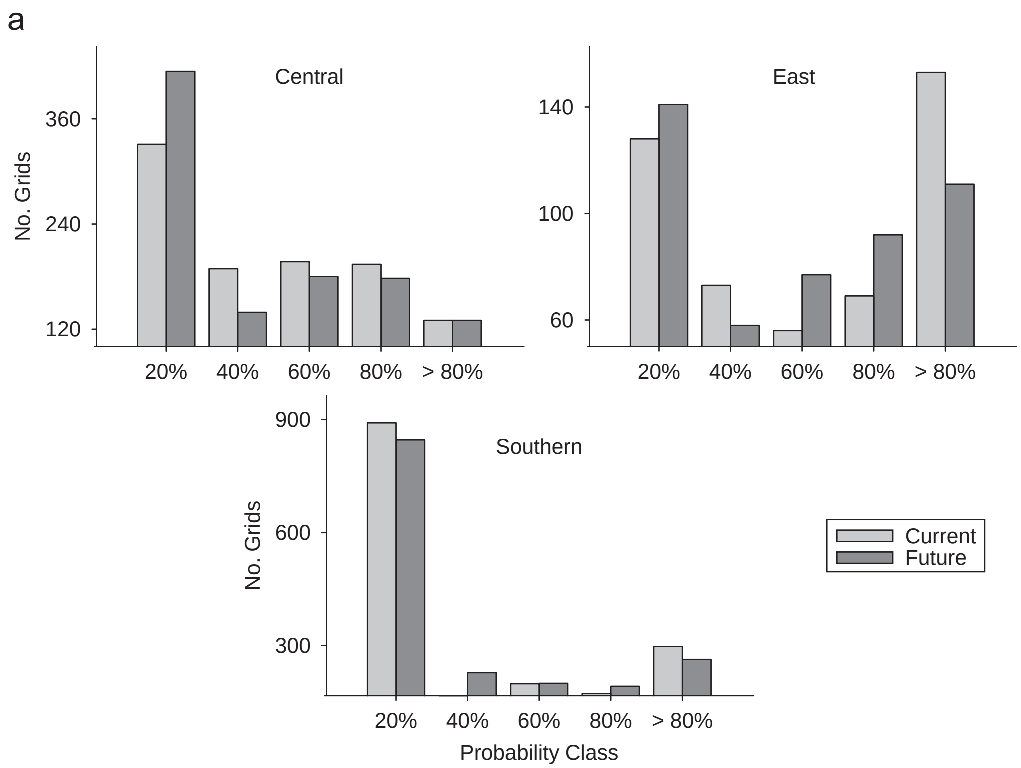

Fig. 3. Changes in the number of *R. appendiculatus* predicted presence grid cells per probability class at regional and country level. (a) Central, East and Southern regions, (b) Burundi, Cameron, Congo, DRC, Kenya, Mozambique and Namibia.

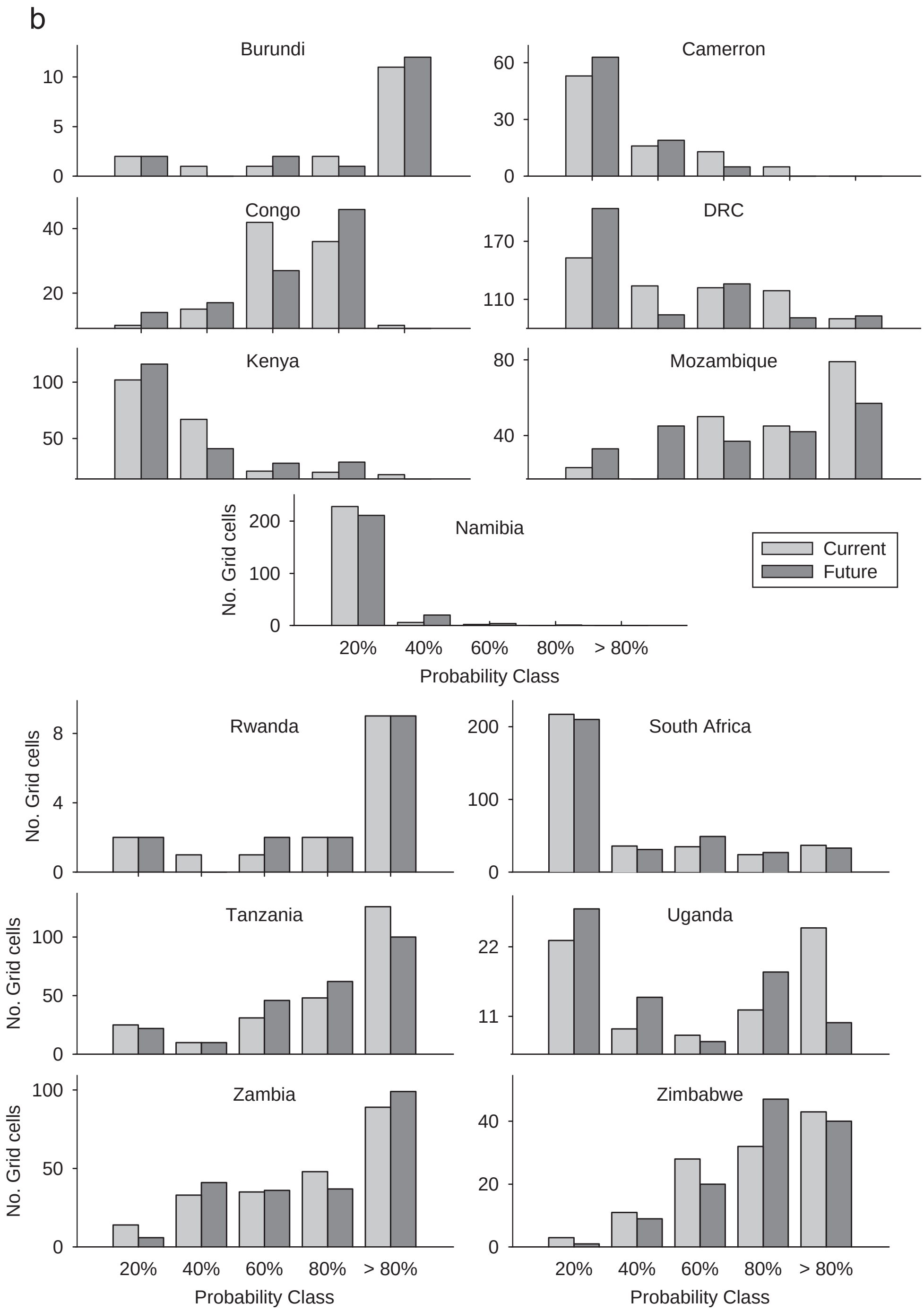

Fig. 3. (*Continued*)

general the size of the *R. appendiculatus* range did not change significantly, the future warmer climate is more suitable for tick infestation as shown by increase in the number of grids in higher probabilities. This situation is particularly true in Burundi, Rwanda, Kenya, Zambia, Zimbabwe and Uganda that show minimal or no change in the predicted number of grid cells in the future climate, but an increase in the number of grid cells in higher probabilities.

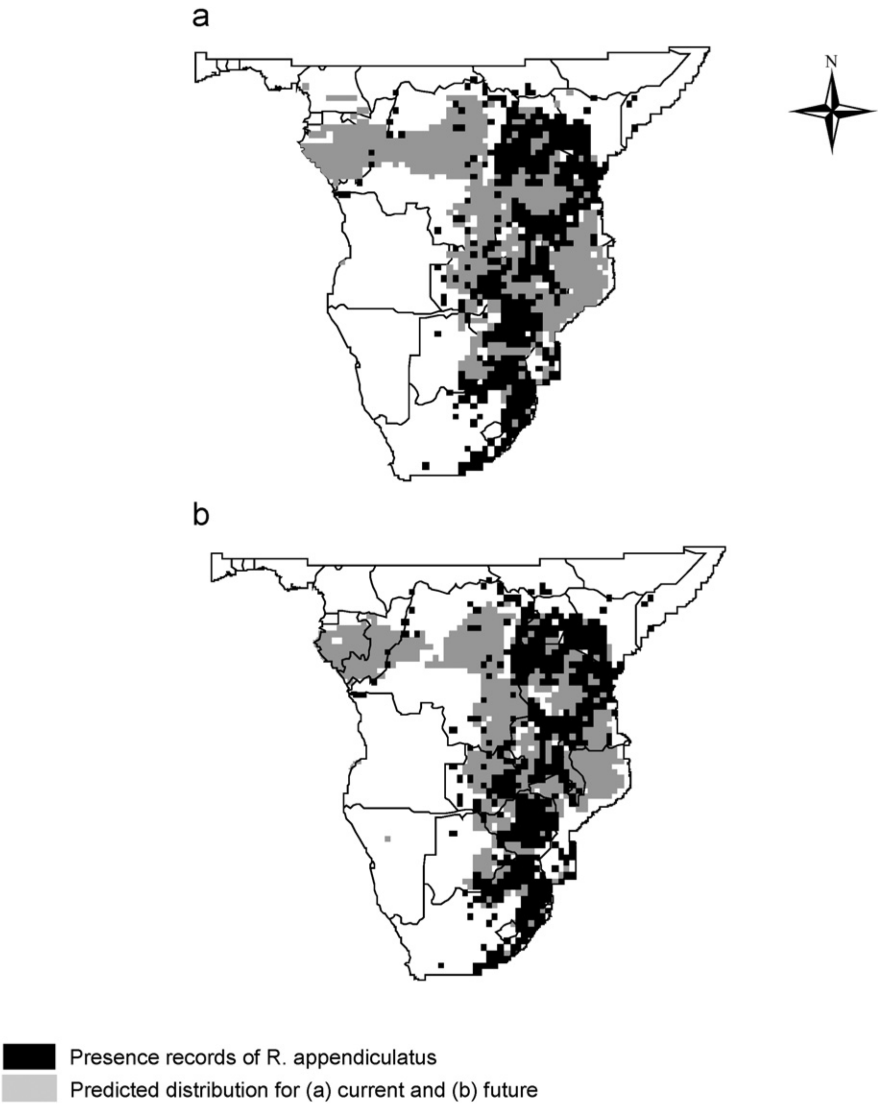

Fig. 4. Predicted current and future *R. appendiculatus* distribution obtained by using the predictive species model (Erasmus et al., 2002) and DARLAM climate surfaces: (a) current, (b) future. Presence assumed at a threshold of 50%.

Predicted increase in ECF suitability in eastern DRC, Botswana, Malawi, and South Africa is in response to the predicted decrease in temperatures during wetter winters (making conditions less harsh) (Botswana and Malawi), and increasing rainfall in the austral summer (South Africa and the eastern DRC). On the other hand, central Tanzania with its predicted future increase in rainfall and slight warming does not show the expected increase in ECF future suitability. This is a clear indication that there are other factors operating at local scales that are also crucial to tick seasonal dynamic such as the absence of the main hosts in this arid part of Tanzania may be responsible for the observable anomaly.

4.1. Data and model limitations

The inclusion of cattle distribution in this model was an improvement on the existing ECF risk maps that are only based on the distribution of *R. appendiculatus*. This was straightforward to do for the current predicted distributions, but for future distribution, it might be useful in future to consider predicted distribution data of cattle. However, predicting cattle distribution changes would need a comprehensive review

Table 4
Number of 60 km × 60 km grids cells for which ECF is present in the predicted current and future distribution at a sub-Saharan and regional scales

Region	Current no. of predicted presence grid cells	Future no. of predicted presence grid cells	No. of overlapping grid cells	Proportional overlap (%)
Sub-Sahara	739	741	639	86
Central	90	102	88	98
East	228	212	191	90
South	401	410	347	87

Proportional overlap values between current and future ranges are also shown. Presence assumed at a threshold of 50%.

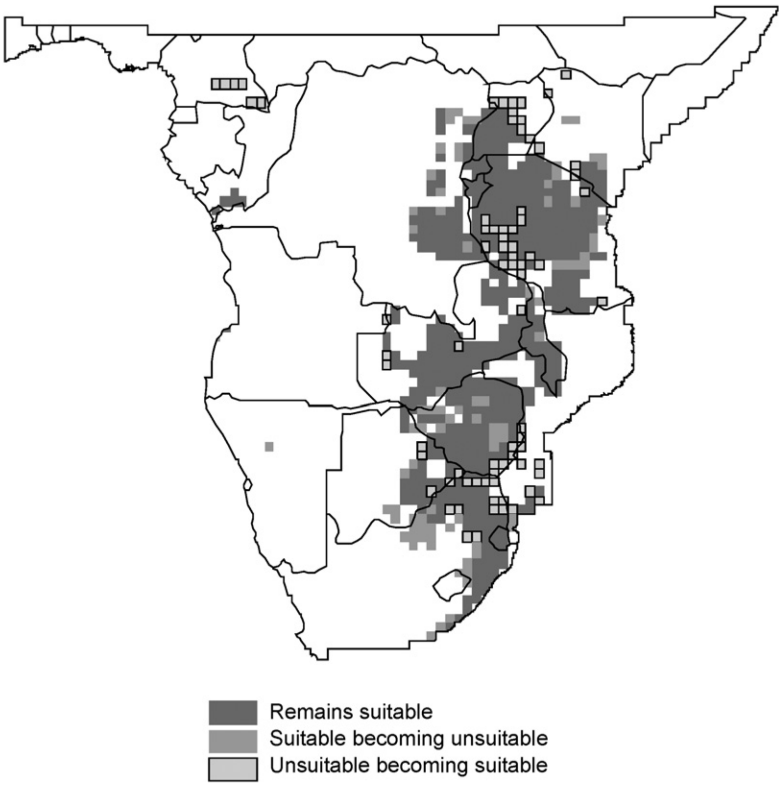

Fig. 5. East Coast fever future risk map obtained by using by the predictive species model (Erasmus et al., 2002) and DARLAM climate surfaces. Presence assumed at a threshold of 50% of *R. appendiculatus* and cattle presence.

and inclusion in the model of at least the following factors: human population distribution changes resulting from population growth and urbanisation; economic changes affecting trade and market development; agro-ecological changes affecting livestock systems, including the impacts of climate change on feed supplies from pastures and crops; and estimation of the effects on livestock production of changes in grazing and land use caused by human use; and finally, an ability to model people's behaviour. Firstly, such elaborate data do not exist at the moment and given the capabilities of the modelling approach used in this study, it is not possible to include all these factors. Furthermore, an analysis of the existing cattle records from 1990–2005 (FAO) showed no significant trends in cattle densities pinpointing to the fact that the part played by climate variability and change in determining cattle densities is not as vital as the one played by non-climatic factors. More importantly, the type of cattle data that we had was not appropriate for use in the predictive species model selected.

Table 5
Number of 60 km × 60 km grids cells for which ECF is present in the predicted current and future distribution at a country scale

Country	Current no. of predicted presence grid cells	Future no. of predicted presence grid cells	No. of overlapping grid cells	Proportional overlap (%)
Botswana	39	44	34	77
Burundi	12	12	12	100
DRC	66	78	64	97
Kenya	20	20	14	70
Malawi	28	31	28	100
Mozambique	45	45	43	96
Rwanda	12	12	12	100
South Africa	78	86	61	78
Tanzania	171	164	150	91
Uganda	37	28	27	96
Zambia	99	99	95	96
Zimbabwe	97	97	80	82

Proportional overlap values between current and future ranges are also shown. Presence assumed at a threshold of 50%.

However, this does not suggest that no change is or will take place in the future because superimposed upon climatic factors, there are other indirect factors operating at different spatial and time scales that have a potential to affect cattle distribution directly or indirectly. Such factors like overpopulation, urbanisation, and industrialisation, land cover and land use change, or the conversion of grazing areas to housing or recreation have not only reduced the available land for cattle rearing, but also blocked migration paths making the impacts of climate change on cattle more severe.

Although the number of heads of cattle or their distribution has not changed (FAO), there are already reported reductions in the size of African Savannas (Scholes and Walker, 1993) through bush encroachments (Roques et al., 2001) as a result of an increase of carbon dioxide. This results in underfed hosts that are more prone to tick infections, because cattle under stress appear to suffer more from each unit of tick attack (Sutherst, 1983). Pastures are also predicted elsewhere to decline in protein levels due to high temperatures and carbon dioxide concentrations, leading to both heavier tick infestations and greater losses for each tick attaching under stressful conditions (Sutherst, 1983). An additional effect may be on the hosts' availability and well being. In this case, cattle may change their distribution in response to climate change. Movement and displacement of some of these hosts may result in changes in host population and/or diversity, which may lead to disruption in life cycles of the tick. This will influence the timing of tick-borne infections and therefore place a huge burden on control programs. With the future availability of the data above and more complex models these results would be significantly improved.

Another important factor not incorporated in this modelling exercise is the vital role that other wild animals play in ECF transmission, even more so for those hosts that act as reservoirs for the protozoan pathogen, *Theileria parva,* that causes this disease. In fact, the use of changes in host numbers to predict disease outbreaks is gaining importance in those diseases whose hosts are clearly known e.g. desert gerbils (*Rhombomys opimus)* and the plague in the Soviet Union (Davis et al., 2004). The findings of the gerbil study confirmed the long-held theory that plague and other infectious diseases erupt when host populations reach a critical threshold. For the plague, bigger populations of hosts make it easy for the vector to jump from one animal to another and the pathogen survives (Davis et al., 2004). Inclusion of the other hosts that are important in ECF transmission is also necessary, but until the controversy regarding host specificity and use of *R. appendiculatus* (Cumming, 2004) is resolved, this procedure will not be applicable for ECF.

The predictive species model used in this paper has been criticised as being unable to incorporate detailed information regarding the factors that influence distribution of tick species and ECF, information which currently does not exist. The model has also been criticised as being simple and static. In most cases a mechanistic model would be the preferred choice. However, Robertson et al. (2003) have shown that an equilibrium type model can perform at least as well, if not better, than a mechanistic model that is based on explicit and known ecophysiological constraints. Such a mechanistic model effectively uses the fundamental niche to determine the bioclimatic envelop of the species; however, if the fundamental niche is not realised at the present, then it is unlikely to be realised in the future. Bioclimatic envelops based on observed distributions effectively capture the realised niches, and are likely to be more adept at predicting future distributions since some measure of factors determining the realised niche is implicitly included (Pearson and Dawson, 2003). Furthermore, this model with its multivariate capabilities as opposed to provision of mere absent–present predictions gives a better estimate especially when dealing with poorly sampled species. Since this can operate effectively using only presence records and any number of climate variables available, it is one of the most practical models since most of the species in sub-Saharan Africa are poorly sampled.

5. Conclusion

The use of predictive distribution models in tick research is still in its infancy, especially in Africa where biological requirements of ticks are not sufficiently known. In this study a profile model that relies only on presence data is used. Tick, climate and cattle data were used in the modelling exercise and in the production of risk maps for the tick species and ECF. The climate data used were simulated by an evaluated nested regional climate data model DARLAM. This study does not suggest that climate is the only factor influencing the distribution of *R. appendiculatus* and ECF. Neither does it mean to imply that the distribution of *R. appendiculatus* and the presence of cattle are the only determining factors for ECF transmission and prevalence. Other factors such as host population size and density, habitat modification, vector control programs and the social environments play a significant role. What this exercise does is to define the role of climate as a factor in determining the potential for establishment when all other factors are not included (Sutherst, 2003) through the development of risk maps that aid control programs, based on a simple, relatively accurate model which does not depend on complicated computing powers. In this paper, we have provided risk maps for the current and future climatic suitability for the establishment of one of the major ticks (*R. appendiculatus*) and tick borne diseases (East Coast fever) in Africa. These risk maps are crucial in current and future control plans of the tick and the diseases. This is because control programs will be targeted to the areas identified. Also from the risk maps, it is possible to provide an early warning system for the disease, making disease management sustainable and cost effective. Although minimal factors influencing the transmission of ECF have been included in this study, we are still of the view that this study has produced significant results in as far as the highlighting the impacts of climate change on the distribution of *R. appendiculatus* and transmission of ECF. The maps and data shown here may therefore not present the actual distribution but support the view presented by Randolph (2002) *that if the objective of a risk map is to warn of potential threat, to alert control services and to direct attention to hitherto uncharted localities where the tick and in this case also the disease may be lurking, it is better to err, within limits of false alarm than of false complacency*.

These results can benefit from the inclusion of ECF distribution records over the last century. More importantly, research into the development of more comprehensive tick models that include both the biological and non-biological factors should be motivated so as to predict not only the distribution ranges but also their reproduction and developmental rates. Country surveys of ticks, hosts and tick-borne diseases should be revived and done regularly so that changes are known at scales. Finally, physical, social and economic aspects of environmental changes must be incorporated in analyses of ticks and tick-borne disease changes in time and space.

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