Climate change and the genus *Rhipicephalus* (Acari: Ixodidae) in Africa

J.M. OLWOCH¹*, A.S. VAN JAARSVELD², C.H. SCHOLTZ³ and I.G. HORAK⁴

ABSTRACT

The suitability of present and future climates for 30 *Rhipicephalus* species in Africa are predicted using a simple climate envelope model as well as a Division of Atmospheric Research Limited-Area Model (DARLAM). DARLAM’s predictions are compared with the mean outcome from two global circulation models. East Africa and South Africa are considered the most vulnerable regions on the continent to climate-induced changes in tick distributions and tick-borne diseases. More than 50% of the species examined show potential range expansion and more than 70% of this range expansion is found in economically important tick species. More than 20% of the species experienced range shifts of between 50 and 100%. There is also an increase in tick species richness in the south-western regions of the sub-continent. Actual range alterations due to climate change may be even greater since factors like land degradation and human population increase have not been included in this modelling process. However, these predictions are also subject to the effect that climate change may have on the hosts of the ticks, particularly those that favour a restricted range of hosts. Where possible, the anticipated biological implications of the predicted changes are explored.

Keywords: Climate change, *Rhipicephalus* species, sub-Saharan Africa, tick-borne disease

INTRODUCTION
The realization that species distributions are significantly influenced by climate has placed considerable emphasis on the need to acquire information concerning the ways in which the present distributions of organisms will be affected by climate change. In response to this challenge, the issue of vector distribution has recently received much attention. Numerous studies (Sutherst & Maywald 1985; Nix 1986; Perry, Lessard, Norval, Kundert & Kruiska 1990; Norval, Perry & Young 1992; Rogers & Randolph 1993; Sutherst, Maywald & Skarratt 1995; Randolph & Rogers 1997; Estrada-Peña 1999; Rogers & Randolph 2000; Randolph 2001, 2002; Erasmus, Kshatriya, Mansell, Chown & Van Jaarsveld 2000; Erasmus, Van Jaarsveld, Chown, Kshatriya & Wessels 2002; Olwoch, Rautenbach, Erasmus, Engelbrecht & Van Jaarsveld 2003; Van Staden, Erasmus, Roux, Wingfield & Van Jaarsveld 2004; Thomas, Cameron, Green, Bakkenes, Beaumont, Collingham, Erasmus, Ferrierra, Grainger, Hannah, Hughes, Huntley, Van Jaarsveld, Midgley, Miles, Ortega-Huerta, Peterson,

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The intimate relationship between climate and the requirements of ticks for survival is well documented (Tukahirwa 1976; Rechav 1981, 1982; Short & Norval 1981; Minshull & Norval 1982; Norval, Walker & Colborne 1982; Dipeolu 1989; Perry et al. 1990; Norval et al. 1992; Okello-Onen, Tukahirwa, Perry, Rowlands, Nagda, Musisi, Heinonen, Mwayi & Opuda-Asibo 1999). This has led to several studies using climate as a means of predicting the distributions of African ticks (Rogers & Randolph 1993; Randolph 1993, 2001; Randolph & Rogers 1997; Norval, Sutherst, Kurki, Kerr & Gibson 1997; Cumming 2000a, b; Estrada-Peña 2001; Olwoch et al. 2003). Collectively the results obtained from these works, some of which used data garnered mainly from interpolated climate databases at 25 km resolution (Perry et al. 1990) or 6 x 6 km resolutions (Cumming 2000b), suggest that accurate predictions of tick distributions at different temporal and spatial scales should be feasible. This approach would be especially useful for predicting the distribution of species in poorly sampled species in poorly sampled regions of Africa.

The genus *Rhipicephalus* is the fourth largest in the Family Ixodidae (Walker, Keirans & Horak 2000), and there are 74 species currently recognized. It is essentially an African genus with approximately 63 species recorded only in the Afro-tropical region and ten species outside the region. One species, *Rhipicephalus evertsi evertsi* Dönitz, 1910, whose distribution was originally confined to the Afro-tropical region has now gained a foothold on the Arabian Peninsula and its distribution is expected to spread even further (Walker et al. 2000). Only 30 species are included in this paper. They are those whose ecological, life history strategies and climatic requirements are relatively well known and, as two distribution data sets have been used, the current distribution of these ticks are relatively well plotted. The way in which these distributions will be influenced by climate change is poorly documented and forms the essence of this paper.

The use of climate-matching models to predict tick distributions

One of the earliest climate matching approaches was CLIMEX, which calculates the climatic suitability of geographic regions for species using a temperature-dependent growth index moderated by four growth indices: hot, cold, dry and wet (Sutherst & Maywald 1985). The use of CLIMEX in northern Australia was considered a great success for predicting the distribution of the tick *Boophilus microplus* (Canestrini, 1887), and it was anticipated that this initial success could be translated into predicting distributions of African tick species. However, early studies tended to over-estimate the distribution of *B. microplus* across Africa, and the predicted high incidence of *Rhipicephalus appendiculatus* Neumann, 1901 in West Africa was at complete variance with the tick’s absence in this region.

Moreover, when the distributions of *Amblyomma* spp. in Africa were modelled using CLIMEX, these were found to be dissimilar to their known distributions. These conflicting results led Norval, Perry, Meltzer, Kruska & Boothroyd (1994) to conclude that the predicted climatic suitability of regions for *Amblyomma hebraeum* Koch and *Amblyomma vari egatum* Fabricius, 1794, is almost the opposite of the actual distribution of these ticks, both in Zimbabwe and in the rest of Africa (Norval, Perry, Gebreab & Lessard 1991; Norval et al. 1992).

BIOCLIM was the second climate-based approach employed to model tick distributions (Nix 1986; Norval et al. 1992). BIOCLIM generates 24 climatic attributes from which annual and seasonal mean conditions, extreme values and intra-year seasonality are derived, for each of a selection of geographic points throughout the distribution range of a tick species. Computer-selected thresholds and limits for each of the indices are matched across a geographical grid to predict potential species distribution. This model generally provided a better fit between the predicted and known distributions of *R.*
appendiculatus, although at a finer scale the match in some areas of the East African highlands was unsatisfactory (Norval et al. 1992). The climate database used was interpolated at an increased resolution (8 km), and this factor alone may explain the improved accuracy when compared to the earlier CLIMEX-based attempts. A subsequent logistic regression approach (Cumming 2000c), based on interpolated climate and elevation data for Africa with a resolution of 25 km (Hutchinson, Nix, MacMahon & Ord 1996) achieved even better accuracy. Such an approach, however, normally requires the existence of a training data set that includes presence and absence information (Estrada-Peña 2003). While it is relatively easy to ascertain where ticks have been collected, it is more difficult to confirm the reliability of surveys in which a tick species is cited as not present. Consequently the assumption that non-presence always implies absence may limit the application of this modelling approach (Estrada-Peña 2003).

The use of an Advanced Very High-Resolution Radiometer (AVHRR) mounted on the National Oceanic and Atmospheric Administration’s (NOAA’s) meteorological satellites was given preference in the 1990s. This instrument allowed the direct detection of environmental factors at an 8 km resolution (Lessard et al. 1990). The main predictor in this procedure is the satellite-derived maximum mean monthly Normalized Difference Vegetation Index (NDVI). However, this technique was reportedly very complicated when used to predict the distribution of R. appendiculatus (Kruska & Perry 1991). There are, however, initiatives to revive confidence in the NDVI approach as a predictive tool in research (Randolph 2002).

The present study used a single species distribution modelling procedure (Erasmus et al. 2000), originally developed by Jeffree & Jeffree (1994, 1996), for predicting species distribution patterns and for evaluating the relative performance of predicted future climate data sets. This model was subsequently modified to accept multivariate inputs to yield probability of presence maps for species (Erasmus et al. 2000). When used to predict the contemporary potential distribution of African ticks (Olwoch et al. 2003) the model achieved positive predictions of more than 70% for the four tick species tested.

**Climate data used for predicting African tick distributions**

The principal sources of climate data for predictive distribution modelling are climate surfaces, generated by interpolating data sampled at varying intensities across a region. Consequently, differences between these climate surfaces can usually be attributed to spatial and temporal evenness of the data used for interpolation. Most modern interpolation techniques are pattern based and statistically incorporate horizontal as well as vertical (altitudinal) adjustments (Hutchinson 1989, 1991; Hutchinson & Gessler 1994). These climate surfaces are, however, relatively smooth because of extensive interpolation between low-resolution point observations.

Another source of climate data is Global Circulation Models (GCMs). These are coupled ocean-atmosphere models that provide three-dimensional simulations of the atmosphere. To date GCMs have produced climate data at a horizontal resolution that is generally too coarse for use in predictive species modelling (> 100 x 100 km grid point resolution), especially for species that are habitat specialists or that are influenced by fine-scale environmental gradients. Computational requirements usually preclude GCMs being run at meso-scale grid resolutions (10–100 km).

The present study used a Division of Atmospheric Research Limited Area Model (DARLAM) as the main climate data set. DARLAM is a potential alternative source of high-resolution climate data that involves the nesting of a high-resolution limited area model within a GCM over the area of interest (for review see McGregor 1997). The GCM supplies the limited area model with initial and boundary conditions. With a grid resolution of 10–100 km, the limited area model is able to simulate some of the meso-scale properties of the circulation model. This technique provides a viable fine scale alternative to the use of observed or interpolated climate surfaces or very coarse scale GCMs climate surfaces. The resolution attained by this dynamic modelling process is essentially limited by the computing power available to the modellers. The implication of using these datasets for predicting current tick distributions has been assessed by Olwoch et al. (2003). In this study, DARLAM’s future predictions are compared with those obtained by using mean climates from two GCMs (CGCM and Centre for Climate System Research/National Institute for Environmental Studies [CCSR/NIES]).

**MATERIALS AND METHODS**

**Study area**

The study area covers sub-Saharan Africa (Fig. 1) and was divided into 3000 grids cells of 60 x 60 km
resolution. This resolution was determined by the
DARLAM climate data.

Tick data
Point localities of tick recoveries were obtained from
Cumming (1999), who compiled the data that he
used from various collections of ticks, and from re-
cent collections made by one of us (I.G.H.). Com-
bining data sets from different sources frequently
compounds identification and distribution errors and
for this reason data congruence with Walker et al.
(2000), who provide well-illustrated distributions of
Rhipicephalus species, was used to assess data
quality in the final compiled dataset. Synonyms pro-
vided by the latter authors also solve the common
dataset problem of referring to one species, but us-
using different names, or referring to a group of spe-
cies as a single species. The tick species selected
for this study belong to the ixodid genus Rhipi-
calus. Species point localities were assigned to partic-
ular 60 km x 60 km grid cells by means of a spatial
intersect in ArcView GIS. A conservative estimate of
the accuracy of these point localities is 0.2° (G.S.
Cumming, personal communication 2003) and con-
sequently this approximation is considered reason-
able. The Rhipicephalus species selected are those
whose distribution and life history strategies are rel-
atively well known and it is our hope that these re-
sults will provide a baseline model for future modell-
ing of other tick species.

Predictive species modelling
A simple climate envelope model was used to pre-
dict the future distribution of the focal species (Eras-
mus et al. 2000, 2002). The input data comprised
3000 grid cells of 60 x 60 km size populated with cli-
mate variables covering sub-Saharan Africa. Reli-
able presence records of the selected tick species
and the present climate values at these locations
were used to construct a climate envelope, using a
principal components-type approach. This climate
envelope represents the range of climates within
which a particular tick is known to occur, and can be
interpreted as the realized niche, as defined solely
by climate. To arrive at a predicted distribution in a
climate change scenario, the existing climate enve-
lope is applied to a climate surface representing fu-
ture climates, and a new geographical interpreta-
tion of distribution is derived (see Erasmus et al. (2000,
2002) and Olwoch et al. (2003) for a more detailed
explanation). This approach was used as a stan-
dardized base for evaluating the relative perform-
ances of the DARLAM and the mean GCM climate
data sets, and allows the creation of a probability
surface of climate suitability for each species mod-
elled.
DARLAM present and future climate data

The Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO) developed the high-resolution limited-area model DARLAM for use in both short-term meso-scale atmospheric studies and longer-term climate simulation experiments (Walsh & McGregor 1995). In the present study ten separate 30-day simulations were performed for both January and July for separate 10-year periods. The periods selected are the 1990s and 2020. The simulations were performed at a horizontal grid resolution of 60 x 60 km using a domain of 100 x 100 grid points that cover sub-Saharan Africa. The monthly average of the ten simulations constitutes the model climatology for the month. The CSIRO Mark 2 GCM was used to force DARLAM at its lateral boundaries. The GCM was integrated for the period 1960–2100, with greenhouse gas forcing corresponding to the A2 SRES (Special Report on Emission Scenarios). The model climate data used in this study were those from the newer IPCC SRES A2 scenario.

Engelbrecht, Rautenbach, MacGregor & Katzfey (2002) illustrated that DARLAM is capable of simulating the regional characteristics of atmospheric variables such as near-surface temperature, low-level wind patterns and rainfall over sub-Saharan Africa with considerable detail. The model does, however, tend to overestimate total rainfall over regions with a steep topography. The DARLAM simulations were performed at the Laboratory for Research in Atmospheric Modelling (LRAM) at the University of Pretoria on a Pentium III workstation with two 550 MHz processors.

GCM future climate data

The GCM climate data used in this study were downloaded from the IPCC/DDC website. Through various stages in ArcView GIS, the original GCM data were processed to fit the 60 x 60 km resolution of DARLAM. The Canadian Global Coupled Model (CGCM2) was the first GCM climate used in this study. It is based on the earlier CGCM1, but with some improvements aimed at addressing shortcomings identified in the first version. In particular, the ocean mixing parameterization has been changed (Gent & McWilliams 1990), and following Flato & Hibler (1992) sea-ice dynamics has been included. The version of CGCM2 used for control and doubled CO2 experiments has ten vertical levels with the lowest prognostic level located at approximately 200 m above the surface. A description of CGCM2 and a comparison, relative to CGCM1, of its response to increasing greenhouse-gas forcing can be found in Flato & Boer (2001). The climate change projections used in this study are those from the newer IPCC SRES A2 scenario.

The second GCM model used was developed by the Center for Climate System Research/National Institute for Environmental Studies, (Japan) (CCSR/NIES) CGCM (Nozawa, Emori, Numaguti, Tsushima, Takeamura, Nakajima, Abe-Ouchi & Kimoto 2001). This model is also based on Emission Scenarios (SRES) of the Intergovernmental Panel on Climate Change (IPCC). It is a Transient Coupled Ocean-Atmosphere Model, which was developed to investigate the direct and indirect climate impacts of the anthropogenic sulphate and carbonaceous aerosols in future projections of climate change. The data used here are from the A2 scenarios. Direct radiative forcing of the carbonaceous aerosols nearly nullifies that of the sulphate aerosols for all scenarios. Estimated total indirect radiative forcing is about –1.3 Wm-2 for the A1, B1, and B2 scenarios, and is about –2.0 Wm-2 for the A2 scenario in the latter half of the 21st Century. Global and annual averages of the surface air temperature increase for all scenarios because of the dominance of the radiative forcing of the increased CO2. Global warming is decelerated with an increase in the anthropogenic sulphate and carbonaceous aerosols, because indirect forcing due to the aerosols has a significant cooling effect. Geographical distribution of the surface warming does not depend much on the scenarios. Cloud feedback becomes dominant in the latter half of the 21st Century, and this introduces further warming at the surface.

Predicting current and future distribution of Rhipicephalus species

The predicted current distributions were initially obtained using current climate predicted by DARLAM. This represents a useful comparison between predicted distributions and known records (see Olwoch et al. 2003). To obtain predicted future distributions the grid cells are populated with future climate variables. The predicted current distributions were obtained using the predictive species model (Erasmus et al. 2000) and six climate variables of current and future mean maximum temperature, mean minimum temperature and mean rainfall of January and July provided by DARLAM. The predicted future distributions were obtained by using both DARLAM and the mean GCM climates. The predictive modelling was executed in S-Plus (S-Plus 2000), while maps of the results were drawn in ArcView GIS. The resultant potential distribution maps represent the probability values of their suitability for ticks based on climate.
Analysis of predicted tick range changes

A number of analyses were performed to compare the predicted current and future distributions of ticks. These included:

(i) Analysis of species range expansion
(ii) An analysis of range contraction
(iii) Change in species richness pattern
(iv) Species range shifts
(v) An assessment of overlap between DARLAM and GCM predicted future distributions.

These range changes were initially analysed for the whole study area and subsequently, in some cases, on a regional basis. In the second analysis, ticks were grouped into the following regions depending on their principal regional distribution, namely East Africa, Central Africa and southern Africa, and a fourth group of ticks that were termed “general” ticks.


There are also species that have wide ranging distributions that overlap in various regions of Africa. These species, termed “general” ticks include R. appendiculatus, R. evertsi evertsi Neumann, 1897, Rhipicephalus pravus Dönitz, 1910 and Rhipicephalus simus Koch, 1844. The above groupings are presented to facilitate interpretation of the current findings and do not imply that the ticks placed in particular geographical regions are restricted to these areas, but rather localise their distribution with extensions into neighbouring regions.

Range expansion and contraction

In order to obtain range changes in terms of contractions or expansions, predicted current or future distributions were first obtained. The predicted current or future distributions were taken as the number of grid cells in which the probability of occurrence is equal to or greater than 50%. The difference in the number of grid cells between the predicted present distribution (DP) and predicted future distribution (DF) constitutes distribution range change (DC). These range changes may either represent contractions or expansions. We initially performed this analysis on a sub-Saharan scale and later on a regional scale in order to establish which regions in Africa would experience greater changes in predicted tick distribution ranges (current and future) and therefore appear more vulnerable to climate change. We analysed the differences between the predicted distributions using the Kolmogorov-Smirnoff two-sample test. Furthermore, we divided the ticks into economically important and unimportant species. A comparison of range changes between the current and future predictions was performed on this latter grouping to assess which of the two groups is more vulnerable to climate change.

In all the above analyses we assessed the proportion of species that experienced expanded or contracted range changes and the degree of the predicted expansion/contraction.

Analysis of change in species richness pattern and degree of range shifts

Species richness patterns were calculated as the number of species in the predicted current or future distribution per grid cell following Erasmus et al. (2002). This analysis was performed for the whole of sub-Saharan Africa. Range shifts were calculated as the number of additional grid cells in the predicted future distribution as a proportion of the current predicted distribution. We used the current predicted distribution instead of current known records because most regions in Africa are poorly sampled.
Comparing predicted future distributions of ticks based on climates simulated by DARLAM and GCM

The accuracy of any climate model is as good as the initial conditions that are used to configure it. Since there is no climate model that provides an accurate projection of the future, it seemed prudent to use the results from more than one climate model in this study. A comparison was therefore made to assess the differences between the predicted future climate suitability for tick species using a regional climate provided by DARLAM and a mean of two GCMs described above. The analysis was performed on a sub-Saharan scale and also on a regional scale. We assessed the degree of proportional overlap between the predicted current distribution and the predicted future distribution (DARLAM and GCM) by means of the proportional overlap method (Prendergast, Quinn, Lawton, Eversham & Gibbons 1993; Reyers, Van Jaarsveld & Krüger 2000). In this case the proportional overlap was calculated as $N_c/N_s$ where $N_c$ is the number of common grid cells between a pair of areas under comparison and $N_s$ is the number of grid cells containing data for both groups or the maximum number of overlapping grid cells possible.

RESULTS

Model Validation was not performed in this study because the same climate envelope model had previously been subjected to rigorous evaluation using presence-absence data resulting from a coordinated and systematic survey effort. Erasmus et al. (2002) used the distribution records of 34 bird species and tested performance of the model using receiver operator characteristic analyses (Fielding & Bell 1997). The model performed significantly better than a random model with no discriminatory ability. It also accurately predicted the complete known distributions for 24 of the 34 bird species, using a 20% sub-sample of the known records (Erasmus et al. 2002). This satisfactory documented performance of the model and the relatively good predictions that were obtained when it was used to predict the current distributions of four African ticks (Olwoch et al. 2003) are sufficient reasons to consider the model adequate for the present study.

Future climate—DARLAM

The climatological anomalies for the 2020s vs the 1990s as predicted by DARLAM are depicted in Fig. 2. January minimum and maximum temperatures are simulated to increase by more than 2°C over certain regions of sub-Saharan Africa. Many 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 be-
come wetter. An interesting feature of the July anomaly fields is that parts of the central subcontinent are simulated to become cooler and wetter.

**Species distribution changes**

*Broad scale range changes* (Fig. 3A, B)

The predicted current and future distributions of the selected *Rhipicephalus* spp. using DARLAM are provided in figures 10–39. On a sub-Saharan scale, the ranges of 46% of the tick species, namely *R. appendiculatus*, *R. capensis* group, *R. distinctus*, *R. humeralis*, *R. kochi*, *R. longus*, *R. masseyi*, *R. ocularis*, *R. planus*, *R. punctatus*, *R. senegalensis*, *R. simus*, *R. zambeziensis* and *R. ziemanni* are predicted to contract. The ranges of 54% of the species, namely *R. aquatilis*, *R. armatus*, *R. bequaerti*, *R. carnivorialis*, *R. complanatus*, *R. compositus*, *R. dux*, *R. evertsi evertsi*, *R. evertsi mimeticus*, *R. exophilmos*, *R. lunulatus*, *R. maculatus*, *R. muehlenensi*, *R. pravus*, *R. pulchellus* and *R. supertritus* are predicted to expand over the same period (Fig. 3A, B). These results translate into an area expansion of 3502 800 km² (12%) in total tick range with a total reduction of 640 800 km² (2%).

**Central African species** (Fig. 4A, B, 16, 17, 19, 25, 26, 28, 34, 35 and 39)

Fifty-five percent of species in central Africa are predicted to show range reductions (*R. longus*, *R. masseyi*, *R. punctatus*, *R. senegalensis* and *R. ziemanni*) while 45% (*R. complanatus*, *R. compositus*, *R. dux* and *R. lunulatus*) are predicted to show range expansions. Although the ranges of the majority of tick species are predicted to contract, the total area of contraction is only 19%, while the total area of expansion by the remaining species is 81%. The tick species predicted to expand its range most in this region is *R. lunulatus* with a total expansion of 252 000 km².

**East African species** (Fig. 5A, B, 11, 12, 13, 15, 23, 24, 27, 29, 31 and 33)

In East Africa 30% of the species (*R. humeralis*, *R. kochi* and *R. planus*) are predicted to show range contractions, while 70% (*R. aquatilis*, *R. armatus*, *R. bequaerti*, *R. carnivorialis* *R. maculatus*, *R. muehlenensi* and *R. pulchellus*) are predicted to show range expansions. This translates into a total expansion of 1 760 400 km² (91%) with a mere 169 200 km² (9%) reduction in total area. The predicted greater expansions are mainly attributable to *R. bequaerti* which
more than doubles its present range and *R. pulchel- 

lus*, which is predicted to expand its range by some 

921 600 km² (49 %).

**Southern African species** (Fig. 6A, B, 14, 18, 21, 

22, 30 and 38)

In southern Africa some 66 % (*R. capensis* group, 

*R. distinctus*, *R. oculatus* and *R. zambeziensis*) of 

the tick species are predicted to contract their rang- 

es. Although only 33 % (*R. evertsi mimeticus* and 

*R. exopthalmos*) of the ticks are predicted to expand 

their current ranges, the total range expansion is 

439 200 km² (23 %) while the total range reduction 

is only 64 800 km² (1 %). Most of the expansion in 

this region is attributable to *R. evertsi mimeticus*.

“General” tick species (Fig. 7A, B, 10, 20, 32 and 

36)

The “general” ticks are those *Rhipicephalus* species 

that are widely distributed with current distributions 

overlapping within various geographical regions of 

the subcontinent. This does not necessarily mean 

that these species are not specialists with regard to 

their ecological requirements, e.g. *R. appendiculatus* 

is confined to parts of eastern, central and south-

eastern Africa (*Walker et al. 2000*). It is a species of 

significant economic importance in Africa because it 

transmits *Theileria parva*, the cause of East Coast 

fever (ECF), which is a major cause of cattle mortali- 

ty and also causes considerable production losses 

cattle in most African countries (*Okello-Onen et al. 1999*). The only tick species predicted to contract its 

range in this group is *R. appendiculatus*, which is 

predicted to contract its range by 212 400 km² (5 %). 

The ranges of 75 % of the ticks in this category, 

namely *R. evertsi evertsi*, *R. pravus* and *R. simus* 

are predicted to expand. The total range expansion 

in this region is equivalent to 864 000 km² (7 %). This 

expansion is mainly associated with *R. simus*, which 

is predicted to expand its range by 601 200 km² 

(70 %).

**Changes in species richness patterns and 

range shifts**

The future climate predicted by DARLAM will alter 

the species richness distribution pattern of African 

*Rhipicephalus*. Compared to the current pattern 

(Fig. 8A) the predicted pattern is spatially different 

and broader (Fig. 8B) with encroachment of ticks 

into new regions. These regions, which include An-
Climate change and *Rhipicephalus* (Acari: Ixodidae) in Africa

gola, Namibia, Botswana and the Northern Cape Province of South Africa, are forecast to experience a more than 50% increase in tick species richness (Fig. 8C). This could be related to increased rainfall in these regions, rendering the south-western regions of sub-Saharan Africa more suitable for ticks. The general west-east shift in species ranges reported by Erasmus *et al.* (2002) is not supported in this study on ticks, in which varying degrees of shift in different directions appears to be the emergent pattern for this taxon. Analysis of range shifts further indicates that 80% of species show less than a 50% range shift, while 20% of species show a range displacement of more than a 100%. The latter species are mainly those that populate the western arid regions of Africa (Fig. 8).

**Species range changes and tick-borne disease implications**

Thirty percent of the ticks included in this study are classified as economically important because they are vectors of diseases of domestic livestock or other animals (Table 1). Although *R. appendiculatus*, the principal *Rhipicephalus* vector of disease in Africa shows range contraction, the remaining vectors are responsible for 52% of the predicted range expansion under future climate conditions. The non-vector species are responsible for 48% of future tick range expansions.

**Predicted future distributions using DARLAM and GCM climate data**

The predictions of future climate suitability for ticks when DARLAM is used are generally more extensive than those generated when using the combined GCM climates. With the exception of four species (*R. compositus, R. evertsi mimeticus, R. exophilus* and *R. oculatus*), and the *R. capensis* group, DARLAM predicts wider ranges of climatic suitability than the combined GCM climate surfaces. DARLAM’s total predictions are 31% broader than the GCMs. The average difference in the range sizes predicted for DARLAM and GCM is 511,200 km². Statistically there is no significant difference between the predictions by DARLAM and GCM using a Kolmogorov-Smirnov test (*P* > 0.1, *n* = 30). However, when the climate data simulated by DARLAM and GCM are analysed for statistical significance, there
### TABLE 1 Rhizophalus spp. and the diseases with which they or the toxins they produce are associated

<table>
<thead>
<tr>
<th>Disease and causal agents</th>
<th>Animal affected</th>
<th>Vectors</th>
</tr>
</thead>
</table>
| East Coast fever (*Theileria parva*) | Cattle | *R. appendiculatus*  
| | | *R. zambeziensis* |
| Tick toxicosis | Cattle | *R. appendiculatus* |
| Corridor disease or Buffalo disease (*Theileria parva*) | Cattle, buffalo | *R. appendiculatus*  
| | | *R. zambeziensis* |
| Gall sickness (*Anaplasma marginale*) | Cattle | *R. evertsi evertsi*  
| | | *R. simus* |
| Equine biliary fever or equine piloplasmosis (*Babesia caballi, Theileria equi*) | Horses, mules, donkeys | *R. evertsi evertsi* |
| Spring lamb paralysis | Lambs, calves | *R. evertsi evertsi* |
| Canine biliary fever or canine tick fever (*Babesia canis*), rickettsiosis (*Ehlichia canis*) | Dogs | *R. sanguineus* |
| Paralysis | Sheep, lambs, calves | *R. lunulatus* |
| Nairobi sheep disease (*Bunyaviridae*) | Sheep | *R. pulchellus* |

### TABLE 2 Proportional overlaps between pairs of grid cells between the predicted ranges from DARLAM and the ranges predicted using mean values for two GCMs

<table>
<thead>
<tr>
<th>“General” tick species</th>
<th>DARLAM 2030</th>
<th>GCM 2030</th>
<th>Common grids</th>
<th>Proportional overlap value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>R. appendiculatus</em></td>
<td>969</td>
<td>858</td>
<td>476</td>
<td>55</td>
</tr>
<tr>
<td><em>R. evertsi evertsi</em></td>
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*Bold* = GCM predictions wider than those of DARLAM
Climate change and *Rhipicephalus* (Acar: Ixodidae) in Africa

FIG. 9 Box plots based on the Kolmogorov-Smirnov test that compared climate predicted by DARLAM and a combined GCM.
FIG. 10–39 Predicted probability distribution of *Rhipicephalus* species using DARLAM and GCM future climates: (A) DARLAM; (B) GCM.

**FIG. 10** *R. appendiculatus*

**FIG. 11** *R. aquatilis*

**FIG. 12** *R. armatus*

**FIG. 13** *R. bequaerti*
Climate change and *Rhipicephalus* (Acari: Ixodidae) in Africa

**FIG. 14**  
*R. capensis* group

**FIG. 15**  
*R. carnivoralis*

**FIG. 16**  
*R. complanatus*

**FIG. 17**  
*R. compositus*