# Remote sensing as a data source in a resource-limited context: species distribution modelling of invasive cattle ticks in West Africa

E.M. De Clercq[1], S.O. Vanwambeke[2]

[1]*Georges Lemaître Institute for Earth and Climate research, Université Catholique de Louvain, Place Louis Pasteur 3, 1348 Louvain-la-Neuve, Belgium, eva.declercq@uclouvain.be*
[2]*Georges Lemaître Institute for Earth and Climateresearch, Université Catholique de Louvain, Place Louis Pasteur 3, 1348 Louvain-la-Neuve, Belgium, sophie.vanwambeke@uclouvain.be*

**Abstract:** Approximately eight years ago, an exotic cattle tick from Latin America, Rhipicephalusmicroplus, invaded West Africa. Ad hoc sampling revealed that it has established viable populations in a few locations in Ivory Coast and through most of Benin.Because of the threat that R. microplus poses toanimal production,several research projects are working on an efficient control strategy, which is based on a map of current and potential distribution. This type of health mapping is part of a long-existing but currently re-emerging field of study that investigates the spatial dynamics of diseases and other health-related issues. Remote sensing and GIS have been essential instruments in this field. In this paper, we illustrate the contribution of environmental variables for disease management in the case of R. microplus, varying from the drafting of a sampling strategy to maps of areas at-risk of invasion for intensive monitoring. Individual Earth Observation images provide only very static information on tick habitat. Often, it is precisely the seasonality of temperature, humidity and vegetation which is important for vector development. NOAA's AVHRR and more recently the MODIS sensor provide this data on a (bi) weekly basis and is an ideal source for tick distribution mapping. Of particular interest for further development are the EO data describing air temperature, humidity, vapour pressure deficit, and soil moisture. In order to be useful forepidemiological applications, this data needs to be available easily and in a standardised manner over large areas, and sufficiently detailed in terms of both spatial and temporal resolution.

**Keywords.** Invasive cattle tick, Rhipicephalusmicroplus, (animal) health mapping, landscape epidemiology

## 1. Introduction

In West Africa,where some of the poorest population live, a large number of people depend on subsistence agriculture and animal husbandry(FAO 2008). These populations suffer from a persistent shortage of animal protein. Milk production by local livestock is low, limited amongst other problems by poor animal health(African Development Bank Group 2008). Cattle are infested by ticks, and susceptibleto diseases caused by tick-borne pathogens, such as Babesiaspp. and Anaplasmaspp. There are several tick species endemic to this region, such as Amblyommavariegatum, Rhipicephalusgeigyii, R. annulatus, R. decoloratus, … and their population and abundance on cattle can be controlled by applyingacaricide treatments(Farougou et al. 2006, 2007).

Approximately eight years ago, an exotic cattle tick from Latin America, Rhipicephalusmicroplus, invadedWest Africa (Madder et al. 2007). Ad hoc sampling revealed that it has established viable populations in a few locations in Ivory Coast and through most of Benin (Madder et al. 2011, 2012, De Clercq et al. 2012). R. microplus is very resistant to acaricides, which leads to inappropriate acaricide use. Because it is usually present in large numbers on individual animals, weight loss due to blood-feeding, diminished milk production and increased mortality are usual problems associated to its presence (Corrier et al. 1979, Guerrero et al. 2007, da Rocha et al. 2011, Madder et al. 2011, Da Silva et al. 2013).Finally, R. microplustransmits both Babesiaspp. and Anaplasmaspp. pathogens more efficiently than the local tick species (Barré and Uilenberg 2010).

Because of the threat that R. microplus poses toanimal production, it is the topic of several research projects being undertaken in the West African region (TickRisk 2012, WecaTic 2012). The main objective of these projects is to propose an efficient control strategy for this invasive tick species in West Africa. In the entire region, officials of the Ministry of Agriculture are urgently demanding accurate maps for estimating the total drug needs and to geographically target control efforts. An essential tool for understanding the problem and allocating control resources is a distribution map, not only able to represent current distribution, but also the areas at risk of invasion. This typeof (animal) health mapping is part of a long-existing but currently re-emerging field of study that investigates the spatial dynamics of diseases and other health-related issues(Hay et al. 2000a). Remote sensing and GIS have been essential instruments of the recent expansion of a field of study that falls in the realm of medical geography(Hay 2000b).

Mapping disease distribution and dynamics can help understand disease aetiologies, andassist informed decision making for disease intervention so that control efforts in endemic situations and intervention strategies in epidemic situations may be directed efficiently(Hay et al. 2000b, Robinson 2000). Disease risk maps allow monitoring and predicting where the next epidemic is likely to begin(Myers et al. 2000).

Contagious diseases, such as influenza, typhus, and measles have been shown to have a strong spatial component. Here, we focus on a particular group of infectious diseases, those transmitted by the bite of an arthropod vector, such as, mosquitoes, ticks, culicoides or sand flies. The distribution and abundance of these arthropods are essential elements to the risk of vector-borne diseases (VBD), and are very much influenced by environmental factors(Bowman and Nuttall 2009).

Local risk maps may be used on the ground to facilitate avoidance action and control operations. Predictions over regional or continental areas are too coarse-scale to direct tactical control, but are required for strategic economic planning and the targeting of national resources within veterinary and public health services(Myers et al. 2000).

Regardless of the vector under study, mapping its distribution based on environmental data always starts with considering the different phases of the life cycle.

### *1.1. Tick ecology*

Ticks have a complex life cycle. They typically have three lifestages: larvae, nymphs and adults. The first two stages are sexless. Larvae and nymphs require a blood meal to moult into nymphs and adults, respectively(Walker et al. 2003). A third blood meal is neededfor the female tick, before she drops to the ground to lay her eggs (Figure 1). The eggs hatch on the ground, and the larvae climb on a cow, where they remain until they drop off as adults. While some tick species drop off the host between each life stage, such as the sheep tick Ixodesricinus, R. microplusstays on the same animal from larva to adult, and is referred to as a one-host or monotropictick. This cycle can be completed in approximately three weeks, but if conditions are not suitable, ticks remain dormant until a more suitable moment to develop into the next life stage.

Direct exposure to environmental conditions happens for R. microplus only between the moment the adult female drops off the host to lay eggs and the moment larvae hatched from those eggs climb on a new host. During their free-living existence they have limited mobility and stay in sheltered micro-habitats on the ground(Randolph 2000). However, one also needs to consider host habitat as well as host mobility (including, in this case, transhumance) in order to understand the tick distribution(De Clercq et al. 2012). This results in the need to consider multiple environmental variables in order to give an exhaustive picture of the risk.

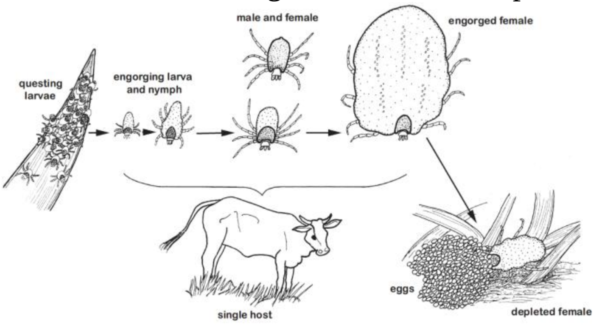



**Figure 1.** One-host life cycle of *R. microplus*(Walker et al. 2003).

In the free-living stage, ticks require grassy vegetation with moist root areas for egg laying and hatching, and the presence of cattle for developing into adults. All life stages are sensitive to drought and high temperatures. The environmental factors determining the distribution are related to temperature,atmospheric/soil moisture and vegetation(Estrada-Peña 2008). Individual measurements on these data provide only very static information. Tick habitats are characterised by specific seasonal cycles in the environment, and (at least) monthly data is needed on e.g. temperature and moisture. While the specifics of habitat or climatic requirements for the various life stages vary between vector species, the broad categories of variable, and the necessity of spatially- and temporally-explicit data is common.

Since all these factors are interrelated with (seasonally varying) cattle presence, mapping tick distribution can be quite a complex undertaking.

A final element that may be considered for mapping the risk of vector-borne diseases are the requirements of the pathogen in the vector, such as in the case of malaria, in which the plasmodium must complete its sexual reproductive stage in the stomach of a female mosquito and migrate to its salivary glands before the mosquito dies. Both parasite development and mosquito survival are influenced by temperature(Hay et al. 2000b).

### *1.1. Tick distribution mapping*

During the last years, distribution maps have been used repeatedly to assist animal health officials in West Africa, as we will describe in this section. We illustrate thus the contribution of environmental variables for disease managementin the case of R. *microplus*.

#### *1.1.1. Country-wide sampling strategy*

Since large-scale infestations were first reported in the south of Benin, geographic support wasrequired for drafting a sampling strategy for a country-wide survey in Benin. Commonly available GIS layers on human population and livestock census data were used. These layers were combined to determine the location of 106 rural villages involved in livestock herding throughout the country, thatwere visited for tick collection.

This cross-sectional tick samplingindicated that R. *microplus* has spread rapidly from the assumed point of introduction in the south of Benin andhas already invaded more than half the country (Figure 2). It is now present in the northern departments, which were previously considered too dry for survival of this tick(De Clercq et al. 2012).

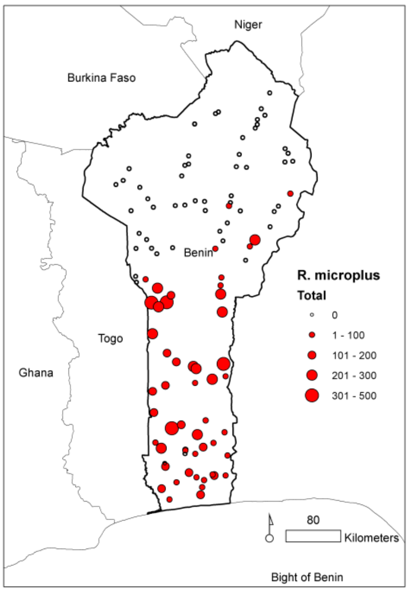



**Figure 2.**Abundance of R. microplusin Benin.Two cows were sampled in each location**.**

#### *1.1.2. Risk maps and targeted surveillance*

A second step was to identify areas in Benin where this tick was likely to survive, given the climatic conditions (De Clercq et al., unpublished results). The WorldClim dataset (Hijmans et al. 2005) was used for modelling. This dataset contains globally interpolated long-term averages for monthly temperature and precipitation at weather stations at a 1 km resolution and is routinely used for disease mapping. The resulting climate suitability maps were used in policy briefs and helped raise awareness on the severity of the problem at the level of decision makers. The fringe of the current distribution is currently monitored to detect further spread.

The climate suitability models of Benin were extrapolated for the entire region of West Africa. These predictions indicated the south of Burkina Faso to be suitable for the survival of R. *microplus.*

## 2. Remote sensing data sources

In the examples given above, existing GIS data layers were used. Although these can be useful for bare-bones applications, they should be used with caution. The amount of reliable data available in most African countries is very limited. Basic data gatheringis performed once every decade in the most optimistic scenario. The last (human) population census in Benin stems from 2002(United Nations Statistics Division 2010), the last census on livestock dates even further back(FAO 2003). While in Europe, weather stations are relatively widespread and data can be obtained relatively easy, this is not the case in West Africa. Benin counts only six weather stations (Thompson 2012)and obtaining their data is a lengthy process. In this context, Earth Observation (EO) data could provide a significant enhancement, providing more timely data and, in the case of climatic data, locally more accurate than the interpolations of meteorological observations. This would also increase the predictive power of species distribution models.

### 2.1. Human population and cattle distribution

Many developing countries struggle to keep close track of human populations, making it difficult to know with fine spatial detail the distribution of humans. The situation is even more complex when considering cattle, especially for highly mobile cattle such as in West Africa. However, knowing the distribution of at-risk individuals (including, as here, cattle not yet infested by R. microplus) is crucial for understanding dynamics and plan control. Several recent initiatives have attempted to fill this major gap by combining various sources of data that often include a satellite-derived land cover component. This helps differentiate areas with low and high population density(Linard and Tatem 2012, Tatem et al. 2012).Cattle distribution maps make use of satellite-derived variables related to climatic conditions to produced spatially detailed and exhaustive maps(Robinson et al. 2007).

### 2.2. Temperature

High temperatures are a limiting factor for R. *microplus*. In the Worldclim dataset, this variable is stored as the maximum temperature recorded in a given month. Acorresponding EO product is available in the MODIS product MOD11A2, giving the land surface temperature (LST) during daytime for a given interval of eight days(USGS 2009).MODIS data of 2011 was used, as this is the year the sampling took place.

In the temperature profile of both WorldClim and MODIS products (Figure 3 and Figure 4), a difference is observed between presence and absence sites in the first part of the year. The tick is limited to relatively cooler sites. When looking at the WorldClim dataset, R. *microplus* is absent from sites featuring temperatures higher than 29°C. Using the MODIS products, the limit is situated at approximately 35°C. Since the MODIS data is not based on long term averages, it presents a less smooth curve.

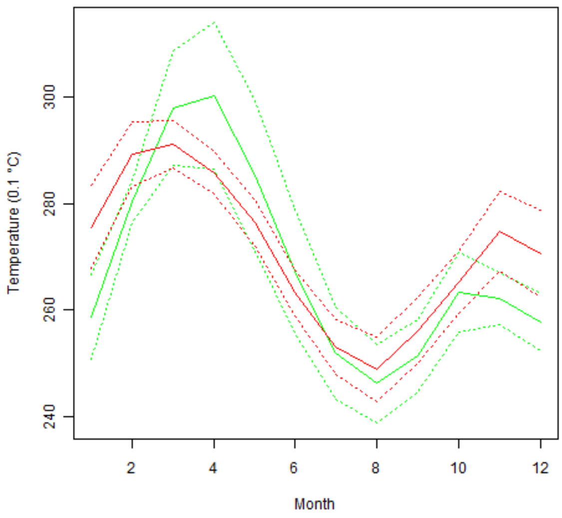



**Figure 3**.Temperature profile from the WorldClim dataset (tmax) at locations where *R. microplus*was recorded absent (in green) or present (in red). Dotted lines represent confidence intervals. The values on the x-axis refer to months.

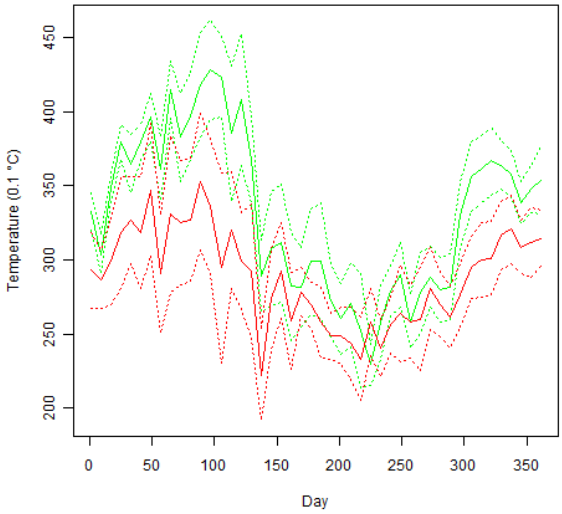



**Figure 4.**Temperature profile from the MODIS product (MOD11A2) at locations where R. micropluswas recorded absent (in green) or present (in red). Dotted lines represent confidence intervals. The values on the x-axis refer to Julian dates.

## *2.3. Rainfall & Moisture*

### *2.3.1. Rainfall*

Rainfall does not directly influence tick habitat, but it provides the necessary humidity. For the presence of R. microplus, it is not the maximum amount of rainfall, or the total rainfall over a year, but again the timing which is important (Figure 5 and

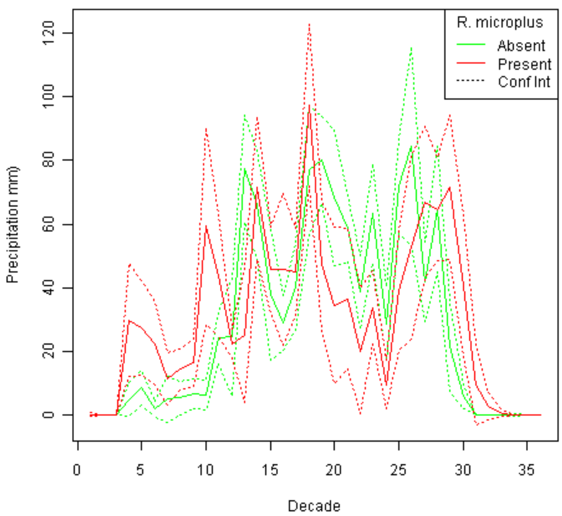



**Figure 6**). R. *microplus* cannot cope with long dry spells. The decadal rainfall data in

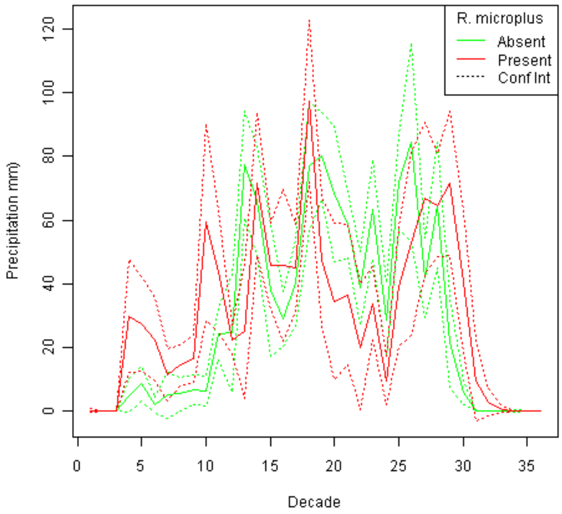
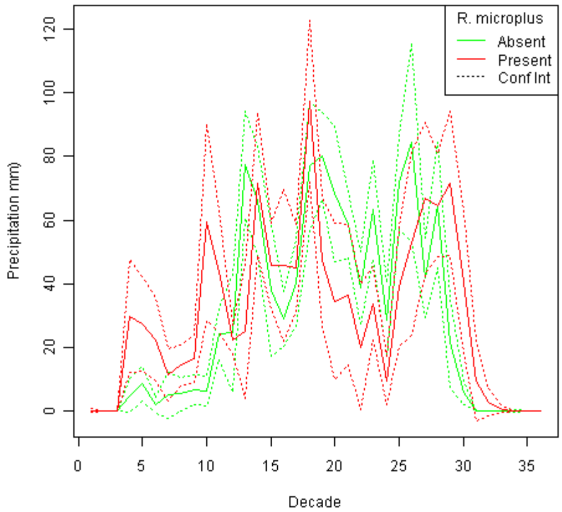
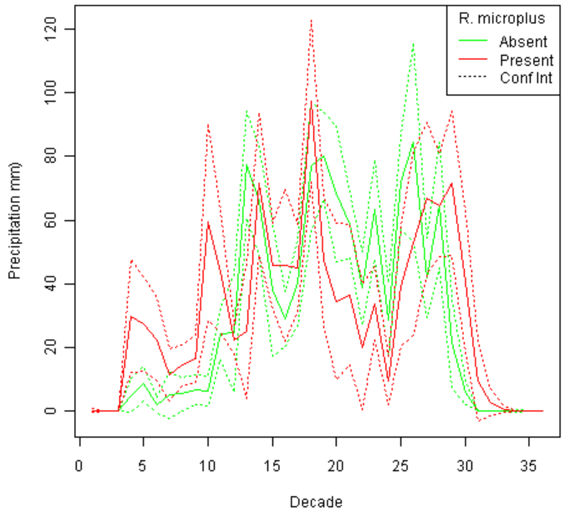



**Figure 6** is very irregular.



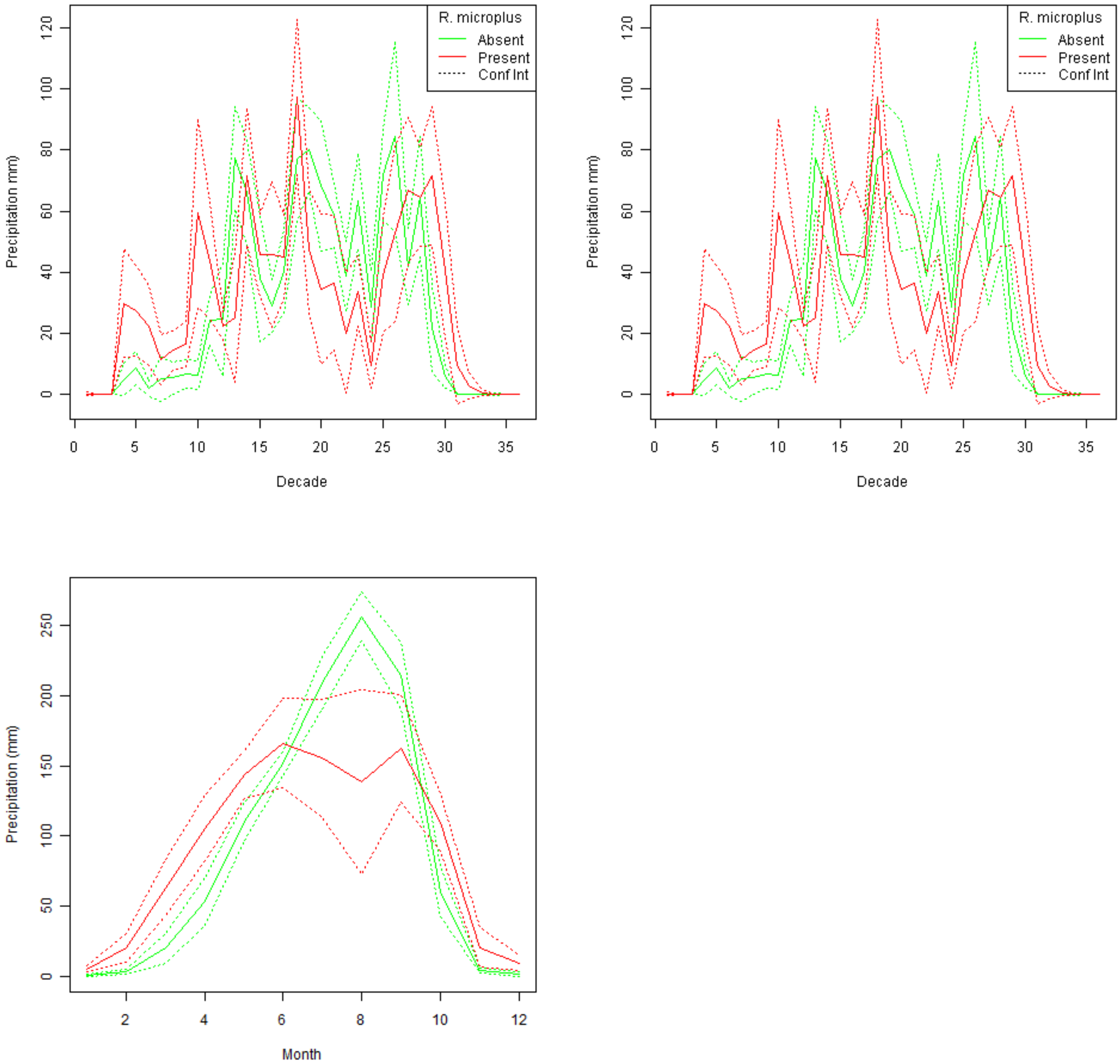



**Figure 5.** Rainfall pattern of the respective presence/absence sites for R. microplusin Benin. Rainfall was based on monthly data in the WorldClim dataset.

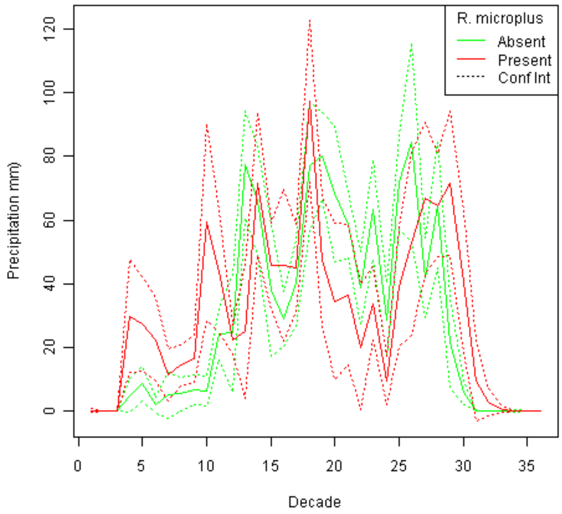



**Figure 6.** Rainfall pattern of the respective presence/absence sites for R. microplusin Benin. Rainfall was based on decadal aggregates of the RFE product.

### *2.3.2. Soil moisture*

For ticks in general, a lack of moisture leads to higher mortality rates(Randolph 2000).Since ticks live closeto the ground, it is logical to consider soil moisture as a limiting factor.

Unfortunately, no widely available method exists to estimate surface moisture routinely with microwave remote sensing. To estimate soil moisture, additional information on the properties of the surface is always needed(van Doninck et al. 2010). This is not a feasible option when working in a resource- and data-limited environment.

### *2.3.3. Proxies for moisture*

NDVI is positively correlated with rainfall or atmospheric relative humidity one or two months before(Randolph 2000). There is thus a sound biological justification for using NDVI as a proxy for climate. Literature indicates that there is a link between NDVI and water saturation deficit(Brooker and Michael 2000).The vapour pressure deficit is the difference between saturation vapour pressure (relative humidity) and the actual vapour pressure and is an indication of the drying power of the air, and is considered by tick experts to be the main driving factor of tick development.AVHRR and more recently MODIS provide this data on a (bi) weekly basis(Goetz et al. 2000).

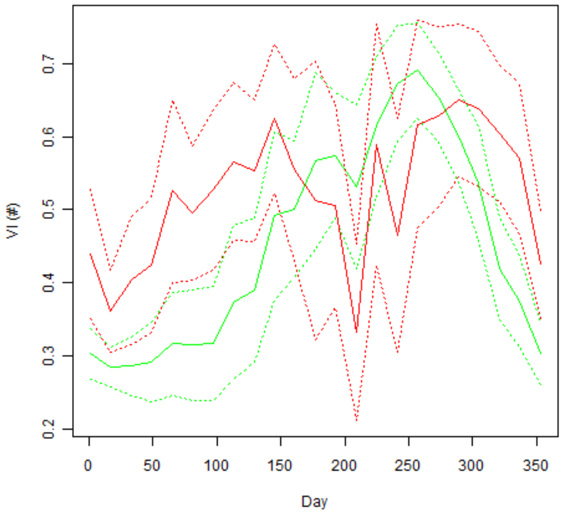



**Figure 7.** NDVI profile of presence and absence sites for R. microplusover the year. The x-axis represents the Julian dates of the NDVI measurements. NDVI was assessed using the MODIS MOD13A2 product.

## 3. Land cover and land use

Vegetation patches with high vegetation (NDVI) and moisture indices have more ticks than those with low values(Randolph 2000). It is therefore possible, at finer scales, to identify land cover types that would be associated with tick presence. Considering the land use types associated to the land covers however may yield further relevant information as land use may correspond to the presence of the tick host, cattle. While focussing on vegetation may already help direct preventive control measures, the most efficient resource allocation would account for land use as well as land cover.

### *3.1. Image processing*

Individual images provide only very static information on tick habitat. Often, it is precisely the seasonality of temperature, humidity and vegetation which is important for vector development(Rogers 2000). Tick habitats are characterised by specific seasonal profiles. Fourier analysis is commonlyused to extract information about seasonal cycles. Not only does this remove noise from the data, but it also results in data reduction. Also, the resulting variables can be interpreted with more biological detail.

## 4. Species distribution modelling

Usingdifferent datasets for environmental variables yields varying distribution results(Regassa 2012). Figure 8 shows the result of species distribution modelling using Worldclim data and Random Forests (RF, for a full description of this modelling technique see specialized literature (Breiman 2001, Peters et al. 2011)). Figure 9 contains the result of RF and MODIS data on LST and NDVI. The Worldclim data only indicates broad trends and tends to underestimate the area at risk of infestation. Using the MODIS data, more spatial detail is available. In the north of the country, climate is too hot and dry for R. *microplus*, but smaller vegetation patches form sheltered habitats and provide a buffer against harsh climate conditions.

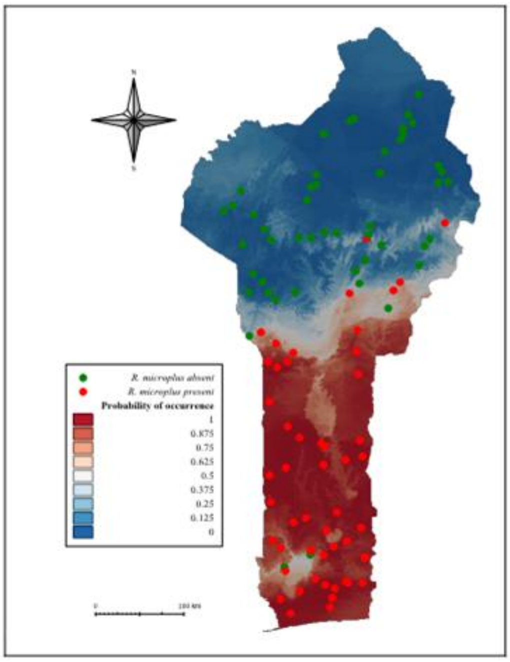



**Figure 8.** Predicted distribution for R. *microplus* based on the WorldClim dataset(Regassa 2012).

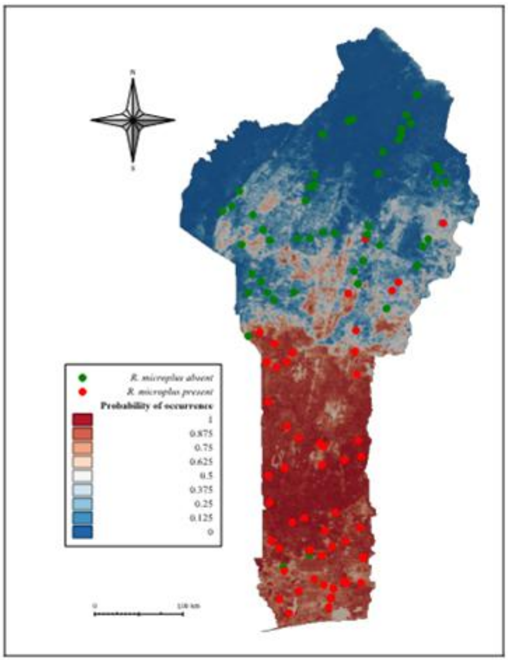



**Figure 9.** Predicted distribution for R. *microplus* based on the MODIS dataset(Regassa 2012).

## 5. Discussion

GIS and EO have only been sparsely been used for animal health mapping, even less in developing countries. The perception that RS and GIS are not appropriate in technologically developing regions persists and is manifest in the form of frequent objections to the cost of image processing equipment, lack of access to imagery, expertise and ground truth and the novelty of the techniques. However, EO data are probably most useful where field data are least accurate, in areas for which little or no data exist, in areas without survey data.

There is significant potential; of particular interest are the EO data describing air temperature, humidity, vapour pressure deficit, and soil moisture. In order to be useful forepidemiological application, this data needs to be available easily and in a standardised manner over large areas, and sufficiently detailed in terms of both spatial and temporal resolution.

Challenges persist with regards to the biological interpretation of remotely sensed variables, and underline the necessity of collaboration between remote sensors, biologists, veterinarians and any other discipline involved. This is the only way that the information available in remote sensing data can be optimally extracted and correctly interpreted. Vector-borne disease systems are complex, because they always involve at least three species (pathogen, host, vector), and therefore considering the environmental requirements of each is relevant. Limiting the study to the requirements of the vector offers an efficient bypass, but interpretation of environmental factors and of spatial risk always requires consideration of the other components of the transmission system.

We should keep in mind that even with advanced techniques and new sensors, values derived from EO data remain approximations of field measurements and proxies for the conditions faced by living organisms. Also, satellite imagery cannot go beyond the present. This highlight the usefulness, still, of weather station data, more easily related parameters produced by future climate models. Still, it is an ideal tool for real-time monitoring of any changes up to the present, and for checking scenarios.

## Acknowledgements

We would like to thank the staff of the Direction de l’Elevage (DE) and the Ministryof Agriculture (MAEP) in Benin for their helpand animated discussionsduring the field work. We are very grateful to all people who assisted us during the tick collection, especially the cattle owners and herdsmen. This work was for a large part funded by the Belgian Science Policy Programs (Belspo, SR/00/144). Recent work has been made possible by a grant from the *Fonds de la RechercheScientifique* de Belgique (FNRS).

## References

[1] African Development Bank Group 2008. Milk and meat sectors support project (PAFILAV). 24.

[2] Barré, N. and Uilenberg, G. 2010. Spread of parasites transported with their hosts: case study of two species of cattle tick. - Rev. Sci. Tech. Int. Off. Epizoot. 29: 135–147, 149–160. 2009. Ticks: Biology, Disease and Control (AS Bowman and PA Nuttall, Eds.). - Cambridge University Press.

[3] Breiman, L. 2001. Random forests. - Mach. Learn. 45: 5–32.

[4] Brooker, S. and Michael, E. 2000. The potential of geographical information systems and remote sensing in the epidemiology and control of human helminth infections.

[5] Corrier, D. E. et al. 1979. Mortality, weight loss and anaemia in Bos taurus calves exposed to Boophilus microplus ticks in the tropics of Colombia. - Trop. Anim. Health Prod. 11: 215–221.

[6] Da Rocha, C. M. B. M. et al. 2011. Perceptions of milk producers from divinópolis, minas gerais, regarding rhipicephalus (Boophilus) microplus control. - Rev. Bras. Parasitol. Vet. 20: 295–302.

[7] Da Silva, J. B. et al. 2013. Influence of the physiological state on infestation by Rhipicephalus microplus in dairy cows. - Ticks Tick-Borne Dis. 4: 52–56.

[8] De Clercq, E. M. et al. 2012. Geographic distribution of the invasive cattle tick Rhipicephalus microplus, a country-wide survey in Benin. - Exp. Appl. Acarol. 58: 441–452.

[9] Estrada-Peña, A. 2008. Climate, niche, ticks, and models: what they are and how we should interpret them. - Parasitol. Res.: S87–S95.

[10] FAO 2003. Report of the Expert consultation on livestock statistics.

[11] FAO 2008. FAO Country information for Benin. in press.

[12] Farougou, S. et al. 2006. Seasonal abundance of cattle tick (Acari: Ixodidae) parasites in the Sudanese part of Benin: Case of the Atacora and Donga Departments. - Ann. Med. Veterinaire 150: 145–152.

[13] Farougou, S. et al. 2007. Tiques et hémoparasites du bétail dans le nord-Bénin. - Rev. Med Vet 158: 463–467.

[14] Goetz, S. J. et al. 2000. Advances in satellite remote sensing of environmental variables for epidemiological applications.
[15] Guerrero, F. D. et al. 2007. Detection of Babesia bigemina infection in strains of Rhipicephalus (Boophilus) microplus collected from outbreaks in South Texas. - Vet. Parasitol. 145: 156–163.
[16] Hay, S. I. 2000a. Remote sensing and geographical information systems in epidemiology. - Academic Press, Elsevier.
[17] Hay, S. I. 2000b. An overview of remote sensing and geodesy for epidemiology and public health application.
[18] Hay, S. I. et al. 2000a. Advances in Parasitology: Guest editors' preface.
[19] Hay, S. I. et al. 2000b. Earth observation, geographic information systems and Plasmodium falciparum malaria in sub-Saharan Africa.
[20] Hijmans, R. J. et al. 2005. WORLDCLIM: Very high resolution interpolated climate surfaces for global land areas. - Int. J. Clim. 25: 1965–1978.
[21] Linard, C. and Tatem, A. J. 2012. Large-scale spatial population databases in infectious disease research. - Int. J. Heal. Geogr. 11: 7.
[22] Madder, M. et al. 2007. Boophilus microplus ticks found in West Africa. - Exp. Appl. Acarol. 43: 233–234.
[23] Madder, M. et al. 2011. Rhipicephalus (Boophilus) microplus: a most successful invasive tick species in West-Africa. - Exp. Appl. Acarol. 53: 139–145.
[24] Madder, M. et al. 2012. New foci of Rhipicephalus microplus in West Africa. - Exp. Appl. Acarol. 56: 385–390.
[25] Myers, M. F. et al. 2000. Forecasting disease risk for increased epidemic preparedness in public health.
[26] Peters, J. et al. 2011. Absence reduction in entomological surveillance data to improve niche-based distribution models for Culicoides imicola. - Prev. Vet. Med. 100: 15–28.
[27] Randolph, S. E. 2000. Ticks and tick-borne disease systems in space and from space.
[28] Regassa, S. L. 2012. Analysis of Habitat Suitability for Rhipicephalus (Boophilus) Ticks in Benin. in press.
[29] Robinson, T. P. 2000. Spatial statistics and geographical information systems in epidemiology and public health.
[30] Robinson, T. P. et al. 2007. The Food and Agriculture Organization's Gridded Livestock of the World. - Vet. Ital. 43: 745–751.
[31] Rogers, D. J. 2000. Satellites, space, time and the African trypanosomiases.
[32] Tatem, A. J. et al. 2012. Mapping populations at risk: improving spatial demographic data for infectious disease modeling and metric derivation. - Popul. Heal. Metrics 10: 8.
[33] Thompson, G. R. 2012. Global Weather Stations. in press.
[34] TickRisk 2012. TickRisk: Assessing ecological suitability for the spread of Rhipicephalus (Boophilus) microplus in West Africa. http://www.elic.ucl.ac.be/repomodx/elic/index.php?id=232. in press.
[35] United Nations Statistics Division 2010. World population and Housing Census Programme. in press.
[36] USGS 2009. MODIS data products, version 05.
[37] Van Doninck, J. et al. 2010. Soil moisture proxies from MODIS-derived apparent thermal inertia time series. 12: 8486.
[38] Walker, A. . et al. 2003. Ticks of domestic animals in Africa: A guide to identification of species. - The university of Edinburgh.
WecaTic 2012. Assessment of emerging livestock ticks and tick-borne disease threats and integrated control strategies in West and Central Africa. http://csiro.coraf.org/en/ticks.php. in press.