

Climate impact on malaria in northern Burkina Faso

Yves M. Tourre,^{1,2} Cécile Vignolles,³ Christian Viel,¹ Flore Mounier⁴

¹Météo-France, Toulouse, France; ²Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY, USA; ³Centre National d'Etudes Spatiales (CNES), Toulouse; ⁴CapGemini Technology Services, Toulouse, France

Abstract

The Paluclim project managed by the French Centre National d'Etudes Spatiales (CNES) found that total rainfall for a 3-month period is a confounding factor for the density of malaria vectors in the region of Nouna in the Sahel administrative territory of northern Burkina Faso. Following the models introduced in 1999 by Craig *et al.* and in 2003 by Tanser *et al.*, a climate impact model for malaria risk (using different climate indices) was created. Several predictions of this risk at different temporal scales (*i.e.* seasonal, inter-annual and low-frequency) were assessed using this climate model. The main result of this investigation was the discovery of a significant link between malaria risk and low-frequency rainfall variability related to the Atlantic Multi-decadal Oscillation (AMO). This result is critical for the health information systems in this region. Knowledge of the AMO phases would help local authorities to organise preparedness and prevention of malaria, which is of particular importance in the climate change context.

Correspondence: Yves M. Tourre, Météo-France, 42 Avenue Gaspard Coriolis, 31100 Toulouse, France.
E-mail: yvestourre@aol.com

Key words: Malaria; Atlantic multi-decadal oscillation; Sahelian rainfall; Climate change; Burkina Faso.

Acknowledgements: the present research was done under the French program Gestion et Impacts du Changement Climatique (GICC APR 2010 – N° 2100214938). Flore Mounier was at the time at the Centre National de Recherches Météorologiques (CNRM)/Météo-France. The authors would like to thank CNES for managing the Paluclim project, and Drs. Philippe Dandin, Philippe Bougeaut former directors of Météo-France Climatology and CNRM divisions. Tourre would like to thank Dr. Sean C. Solomon director of Lamont-Doherty Earth Observatory (LDEO) for supporting his research. This is LDEO contribution #8149.

Received for publication: 30 June 2017.
Revision received: 9 October 2017.
Accepted for publication: 17 October 2017.

©Copyright Y.M. Tourre *et al.*, 2017
Licensee PAGEPress, Italy
Geospatial Health 2017; 12:600
doi:10.4081/gh.2017.600

This article is distributed under the terms of the Creative Commons Attribution Noncommercial License (CC BY-NC 4.0) which permits any noncommercial use, distribution, and reproduction in any medium, provided the original author(s) and source are credited.

Introduction

The latest decades have shown changes in the climate, which may eventually have large-scale consequences for the frequency distribution of vector-borne diseases. The French Paluclim project (Vignolles *et al.*, 2016) applies a tele-epidemiology conceptual approach linking climate and environment in studying the impact of frequency deviations of infectious diseases like malaria. The potential of climate change to influence vector behaviour is strong, and the first signs would be expected in north-western Africa, such as in the Sahelian Nouna region in Burkina Faso where a variation in the pattern of rainfall has already been observed. The impact of low-frequency variability and change of environmental conditions with respect to malaria risk would constitute the first step for understanding any changes of malaria outbreaks and it would also contribute decisively to the local health information system. Validation of any dynamic entomological risk maps found, including vector adaptation, is needed and it should be implemented to address predicted risks and thereby establish a better foundation for disease control. To achieve this, the Paluclim project integrated efforts from several teams and partners: including the French Space Agency (CNES), the French Weather forecast agency Météo-France, the Public Health Institute of the University Hospital of Heidelberg, Germany) and the Centre de Recherche en Santé de Nouna Burkina Faso. Former experience and expertise obtained by the different partners regarding entomology, climate, environmental sciences and tele-epidemiology (Marechal *et al.*, 2008) were taken into account.

Some of the results presented here derive from the Paluclim project. The overall aim of this particular study was to analyse the climate impact on the local malaria vectors and to investigate the rural risk of malaria infection in the Nouna region in the Sahel administrative territory of northern Burkina Faso. Important objectives were to elucidate the consequences with respect to the entomological risk scenarios and public health, and to study the variability of climatic impact on malaria risk at various scales.

Materials and Methods

Study area

The study was conducted in the Nouna region (4.1°/3.5°W and 12.4°/13°N) in northern Burkina Faso (Figure 1).

Climate data

Datasets from Africa Rainfall Climatology version 2 (ARC2) were used for rainfall and datasets from the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis (ERA-interim) (<https://www.ecmwf.int/en/research/climate-reanalysis>)

for temperature (T_n for minimum and T_x for maximum) and relative humidity (RH), all for the 1983-2011 period that was utilised for this study. The datasets were statistically homogeneous for the period under study. Monthly climatology could thus be derived for these four parameters (Figure 2). The height of the rainy season, characterised by maximum rainfall, minimum T_x , and maximum RH (highlighted by a red rectangle in the figure), was identified to occur from July to September. The minimum temperatures T_n occurred in December and January when the infra-red radiation from Earth is at its maximum due to prevailing clear skies (highlighted by a red circle in the figure).

The chronological series (z-series) for the different parameters were obtained by computing their mean values at the four grid-points constituting the corners of the frame of the Nouna region. Bias, spatial correlation, median absolute errors (MAE) and root-mean-squared errors (RMSE) were also been computed for each series for the region. We used an impact model to assess the impact of climate conditions on malaria risk.

This approach follows the work of Craig *et al.* (1999) and Ermert *et al.* (2011) modified by Tanser *et al.* (2003) when applied in the project mapping the malaria risk in Africa (MARA). The indices for malaria diffusion were based on rainfall, temperatures (min. and max.) and RH data computed from the impact model, with values of 0 for unsuitable conditions (U) and of 1 for suitable conditions (S).

Results and Discussion

For rainfall, the bias varied between -1 and +1 mm. The largest gradient occurred between April and October and was generally located in the North, indicating that the corresponding z-series generally over-evaluates rainfall in that area. Moreover, for reasons that could be due to seasonal wind reversal, the axis for the maximum gradient was oriented in the direction southwest to northeast in April, July and August and northwest to southeast in May-June and September (not shown). It should be noted that during the rainy season, correlations between the z-series and the time series obtained at the four grid-points surrounding the study area were larger than 0.75. The best correlations were found in June. The MAE was <3 with a small RMSE (<8) with very little spatial variability.

The bias for temperature was between 0 and -1°C for T_n and T_x , respectively. During the rainy season, correlations between the z-series and the time series at the surrounding grid-points were larger than 0.95. For the RH the bias varied between +4 and -4% with a significant gradient from March to September. However, the z-series over-estimated humidity in the North, which is due to the fact that the Nouna region is, in general, dryer under the influence of the continental trade winds (the harmattan) and more humid in the South due to the association with the southwest monsoon. Correlations between the z-series and values at the grid-points

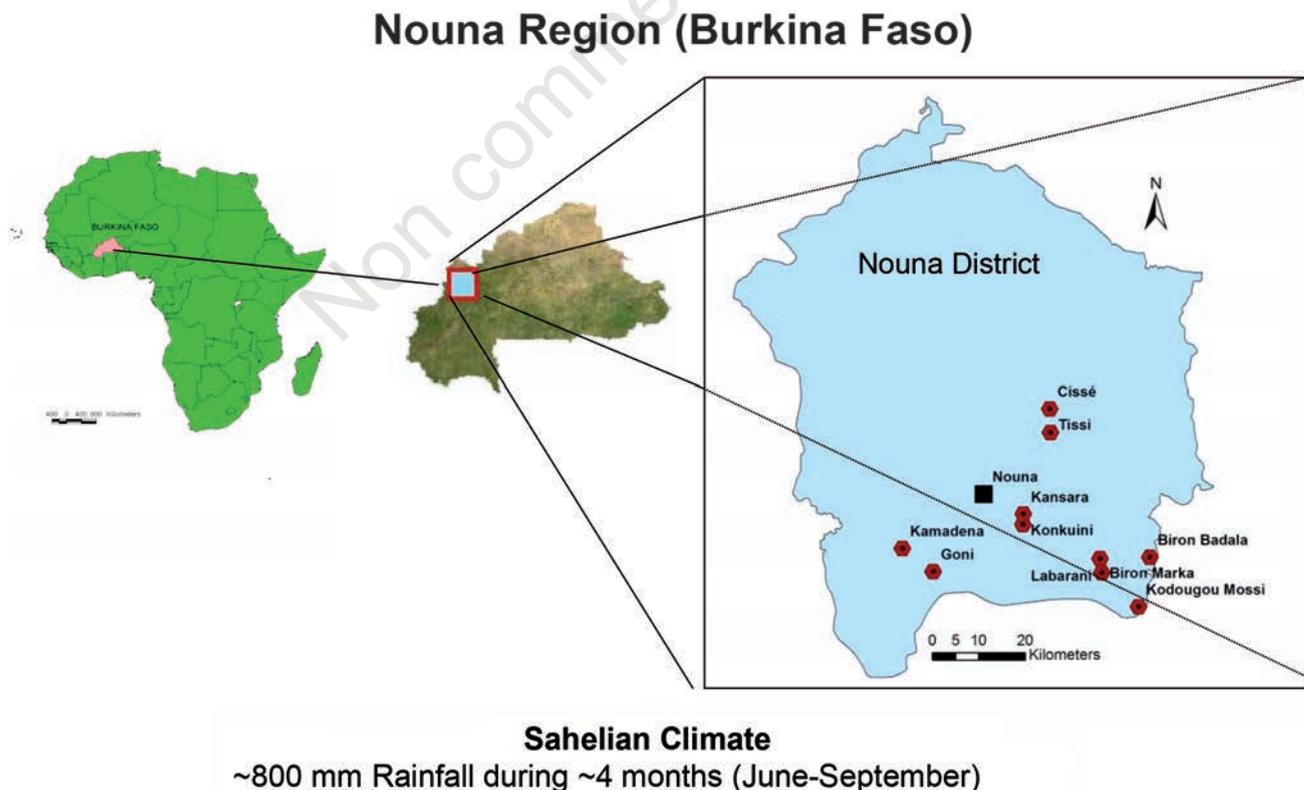


Figure 1. Localisation of the region of Nouna in Burkina Faso, West Africa.

were larger than 0.97. Very little information was lost by using simple, straightforward averaging from the four points around Nouna. For easy comparison, all four parameters and their mean annual evolution of monthly climatology are displayed for the 1983-2011 period (Figure 3). During the height of the rainy season (June to September) the absolute minima for T_x and the RH maxima were well identified. There was also a relative minimum for T_n , with absolute minimum values during December and January.

Climate analysis and malaria risks

It was recognised that the use of indices is an over simplification since other parameters, such as vector densities and human

susceptibility, are also involved with infectious diseases. The entomological mapping from the Paluclim project integrates such complexity by looking at environmental factors and at the larval and adult stages of the vectors. It should be noted that the indices thus cannot be directly compared to *in situ* data and they do not take into account vector aggressiveness. Nevertheless, it was felt that the simple approach used allows for a relevant diagnostics of the malaria diffusion under different local climate conditions and temporal scales.

According to Craig *et al.* (1999), the suitable conditions (S), mainly linked to the temperature, were obtained from studying the relationship between temperature and sporogony, vector survival

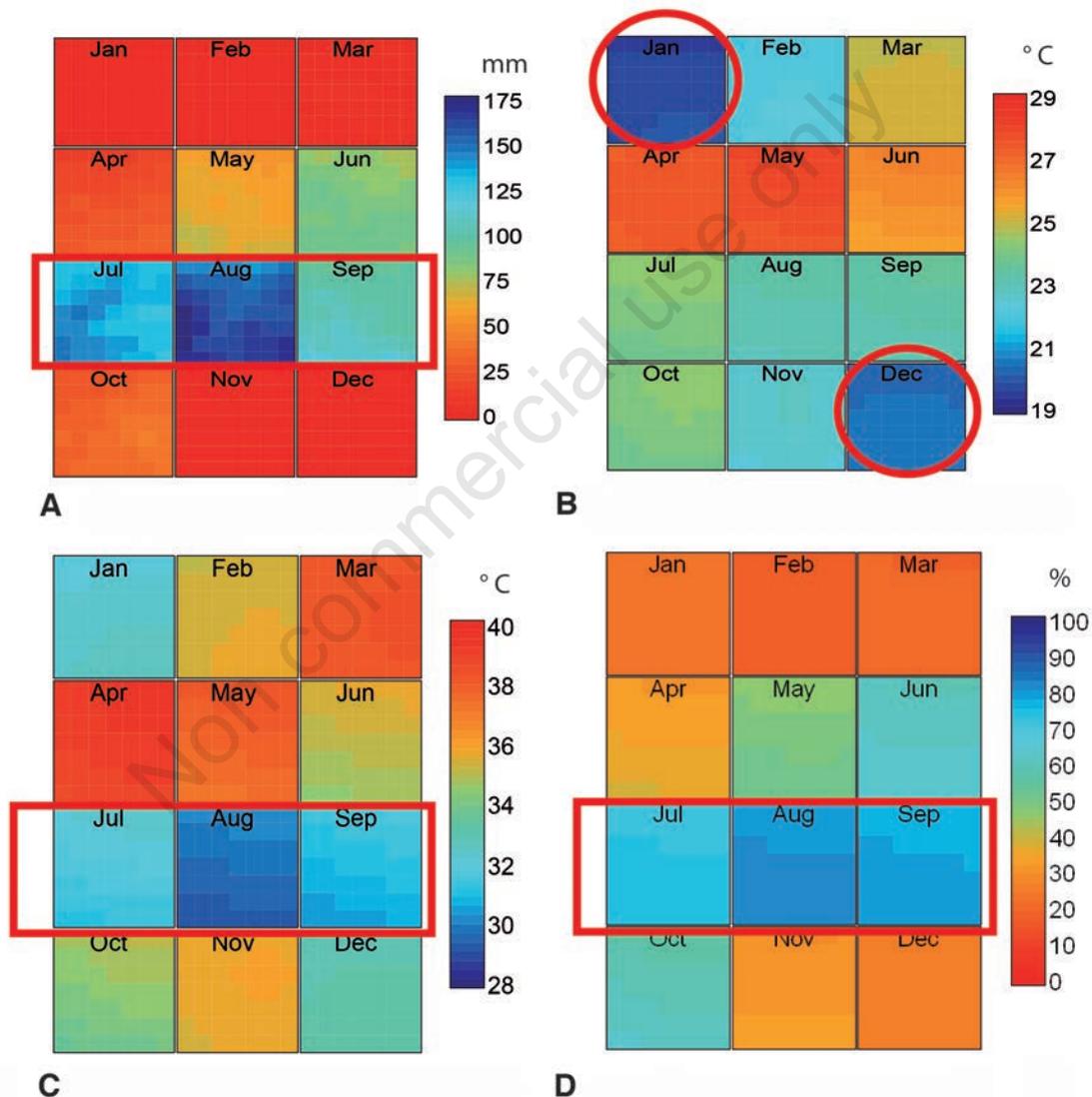


Figure 2. Monthly climatology 1983-2011 for Nouna, Burkina Faso with reference to accumulated rainfall, averaged minimum and maximum temperatures and relative humidity. A) Monthly rainfall climatology in mm. The range is from 0 (dark red in November-March) to 175 mm (dark blue in August). Red rectangle is for at least three consecutive months with maximum total rainfall values. B) Monthly minimum temperature climatology T_n in °C. The range is from 19°C (dark blue in January) to 29°C (dark red in May). Red circles are for months with minimum values. C) Monthly maximum temperature climatology T_x in °C. The range is from 28°C (dark blue in August) to 40°C (dark red in April). Red rectangle is for consecutive months with maximum values. D) Monthly mean relative humidity in %. The range is from 0 (dark red in February) to 100% (dark blue in August). Red rectangle is for consecutive months with maximum values.



and length of the larval cycle. The most favourable conditions are the zones totally excluded from dry periods. An analysis of the rainfall amount made clear that a given threshold is necessary to start an epidemic. Lack of, or minor, rainfall amounts are therefore the primary limiting factor. Craig *et al.* (1999) claim that three months of rain might be sufficient for suitable S-conditions in Mali. Moreover, the three-month period must display an accumulated amount of rainfall larger than 80 mm to achieve favourable conditions. Since Mali and Burkina Faso are neighbouring countries in the Sahel, a malaria seasonality model (MSM) was developed along the lines published by Tanser *et al.* (2003) for the MARA project. It was found that only one month above the threshold of 80 mm of rain was necessary here, whilst the two other months must have thresholds of at least 60 mm. As can be seen in Table 1, the meteorological parameters could be converted into U or S conditions by monthly valuation. Thus a malaria epidemic would be possible if the accumulated rainfall of one month were ≥ 80 mm followed by at least two other months with >60 mm of rain. Therefore, three-month sliding sequences with $S=1, S>0, S>0$ must also account for the number of adjacent days of continuing rainfall as well as the presence of dry long periods between intense

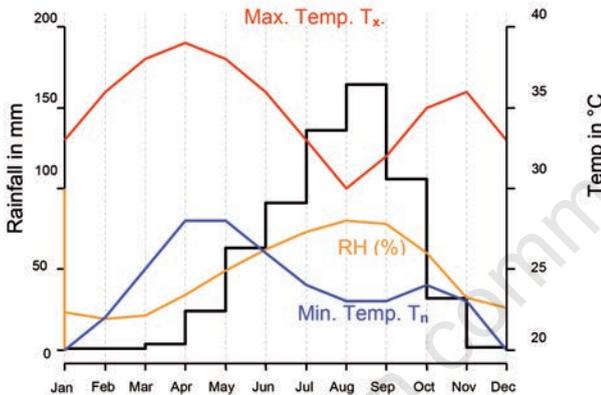


Figure 3. Monthly climatology in the Nouna region, Burkina Faso (z series) averaged for 1983-2011. Accumulated rainfall (histogram) is in black, relative humidity (in %) is in orange, maximum temperature is in red and minimum temperature in blue.

YEAR	Rainfall					Relative Humidity					Temperature													
	May	June	July	Aug.	Sept.	Oct.	May	June	July	Aug.	Sept.	Oct.	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1983			X	X			0.0	90	100	100	100													
1984			X	X	X		2.4	50	100	97	93	42												
1985			X	X	X		0.0	67	100	100	100	39												
1986	X	X	X	X	X		4.0	39	80	100	100	48												
1987	X	X	X	X			3.0	93	97	100	100	61												
1988			X	X	X		3.0	63	100	100	100	39												
1989			X	X			2.8	40	97	100	100	32												
1990	X				X		2.9	57	100	100	100	55												
1991	X				X		0.0	55	73	100	100	58												
1992			X	X	X		0.0	26	90	97	100	58												
1993	X	X	X	X	X		4.0	43	87	100	100	58												
1994			X	X	X		3.0	60	100	100	100	100												
1995			X	X	X		2.0	39	70	94	100	58												
1996			X	X			2.2	73	84	100	100	74												
1997	X	X	X	X	X		4.0	35	90	100	100	71												
1998	X	X	X	X	X		4.5	23	73	97	100	74												
1999	X	X	X	X	X		4.0	20	100	100	100	88												
2000	X	X	X	X	X		4.8	63	94	100	100	39												
2001	X	X	X	X	X		4.0	80	100	100	100	32												
2002	X	X	X	X	X		5.0	33	87	100	97	45												
2003	X	X	X	X	X		5.0	87	100	100	100	71												
2004	X	X	X	X			3.0	43	97	100	100													
2005	X	X	X	X			4.0	60	100	100	100	45												
2006	X	X	X	X	X		6.0	27	90	100	100	90												
2007	X	X	X	X			4.0	40	100	100	100	13												
2008	X	X	X	X	X		5.0	47	100	100	100	48												
2009	X	X	X	X	X		6.0	50	97	100	100	77												
2010	X	X	X	X	X		5.3	19	77	94	100	100												
2011	X	X	X	X	X		4.0	50	87	100	100	58												

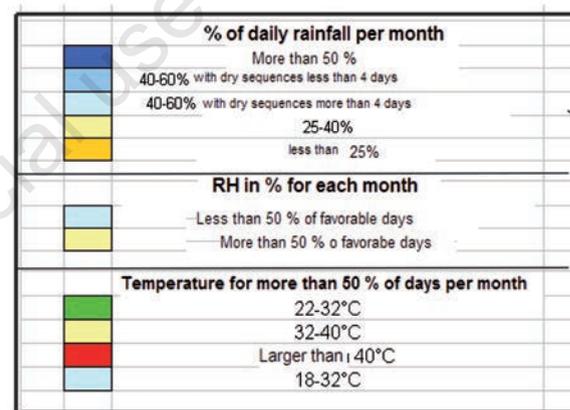


Figure 4. Temporal mapping of climate conditions with respect to the impact of rainfall, relative humidity and temperature for malaria diffusion. Monthly values for rainfall, relative humidity and temperature conditions for each month and year during the 1983-2011 period. The transitional year of 1996 is highlighted. Calculated annual indices are blue in the last column of the rainfall table.

Table 1. Conditions governing malaria diffusion.

Variable	Range	Index value	Unfavourable condition	Suitable condition for malaria diffusion
Monthly rainfall (mm)	>80	1		
	≥ 60 and <80	Equation 1°	60	80
Monthly values of T_n and T_x (°C)	<18 or >40	0		
	≥ 22 or ≤ 32	1		
	>18 and <22	Equation 2#	18	22
	>32 and <40	Equation 1°	40	32
Monthly value of relative humidity (%)	<60	Equation 2#	0	60
	≥ 60	1		

$$^{\circ} = \cos^2 \left[\frac{x-S}{U-S} \times \frac{\pi}{2} \right] \text{ with } S < x < U; \quad \# = 1 - \cos^2 \left[\frac{x-U}{S-U} \times \frac{\pi}{2} \right] \text{ with } U < x < S.$$

rainfall events. The use of such sequencing allowed us to get values for an annual index for suitable rainfall conditions by summing results for consecutive months obtained from equations 1 and 2 (0 to 1 for each month). Values from 0 to 6 were thus obtained during the 1983-2011 period.

All results are displayed in Figure 4 with months without mean favourable conditions shown in white. For rainfall data, X indicates that the monthly total rainfall is >80 mm; red shade cross-marks the first month of rainfall conditions. The years in red (left column) are those when favourable conditions were never attained. A conspicuous sudden increase in the calculated index values for rainfall (last column in blue with values from 0 to 6) can clearly be seen after 1996 where values for the indices are larger than 3.0 from 1997 until 2011. The detailed colour-key code for Figure 4 is given just below it. Once again the indices appear in blue when conditions are favourable. Insofar as the temperature is concerned, April was the hottest month ($>40^{\circ}\text{C}$) and August the coolest by far, with maximum temperatures between 22°C and 32°C (except in 1984, 1987 and 2004), whilst the RH was 100% in August and September.

Figure 5 displays the rapid changes for the rainfall data differently. Values of the calculated annual index below or over 3.0 (after 1996) are indicated by a horizontal black line. Since the accumulated rainfall is the limiting factor two rainy periods modulated by a low-frequency signal may be highlighted: one from 1983 until 1996 starting with short rains and small rainfall amounts (*i.e.* similar to rainy seasons shorter than normal) and the second period from 1997 until 2011 with higher accumulated rainfall amounts. The latter period is thus much more favourable for malaria transmission.

Natural rainfall variability and climate indices

The index values for the last 30 years indicated the monthly total rainfall as the most important parameter modulating the malaria conditions in the Nouna region. It thus became a prerequisite to highlight the climate conditions (at different timescales) associated with this variability on a monthly to seasonal basis, including low-frequency/secular variability prior to and after 1996.

Seasonal and intra-seasonal variability were tested using statistical techniques and numerical models. One of the known climate signals is the low-frequency, secular oscillation called the Atlantic Multi-decadal Oscillation (AMO), which underwent a phase-change in the mid-1990s and is known to modulate the Sahel rainfall (Zhang and Delworth, 2006; Paz *et al.*, 2008). With a one-month lag, the correlation between rainfall in the Nouna region and the AMO for July-September (JAS) and August-October (ASO) was 0.66 and 0.69, respectively.

The AMO is associated with the low-frequency oceanic thermohaline oscillation (Knight *et al.*, 2005) with one of its signatures being the variability of the sea surface temperature (SST). The oscillation range is 50-70 years in the Atlantic Ocean ranging from latitude 60°N to the equator and from longitude 75°W to 7.5°W (see Enfield *et al.*, 2001 and regarding the index at <http://www.esrl.noaa.gov/psd/data/correlation/amon.us.data>). Basically, the AMO index was negative from 1960 until 1995 and became positive from 1996 and continues to be so. Negative values of the AMO are associated with the latitudinal position of the Inter-Tropical Convergence Zone (ITCZ) and a decrease of Sahelian rainfall in the southern direction, while positive values correlate with an increase in the northern direction (Tourre *et al.*, 1999). As mentioned above, the latter also agrees with rainfall conditions

favouring low-frequency malaria conditions and variability.

There is also a North Atlantic Oscillation (NAO), defined by Bjerknes (1964) as a climate oscillation influencing the entire North Atlantic Ocean. The variability is based upon the difference between the sea-level pressure of the Azores anticyclone (data from stations in Lisbon or Ponta Delgada or Gibraltar) and the Icelandic low-pressure system (data from stations in Reykjavik, Stykkisholmur or Akureyri). During the negative phase, the jet stream is found further to the South, while North and West Africa are under the influences of more humid air masses than normal. The NAO displays a definite quasi-decadal variability and was used for the modelling experimental prediction (see below). With a one-month lag, the correlation between rainfall and the NAO for JAS and ASO was -0.56 and -0.52, respectively based on the National Oceanic and Atmospheric Administration (NOAA) index from the NOAA Climate Prediction Center (CPC) (<http://www.esrl.noaa.gov/psd/data/correlation/nao.data>)

Also other climate indices have been tried but have so far they not delivered significant results. Nonetheless, future diagnostic

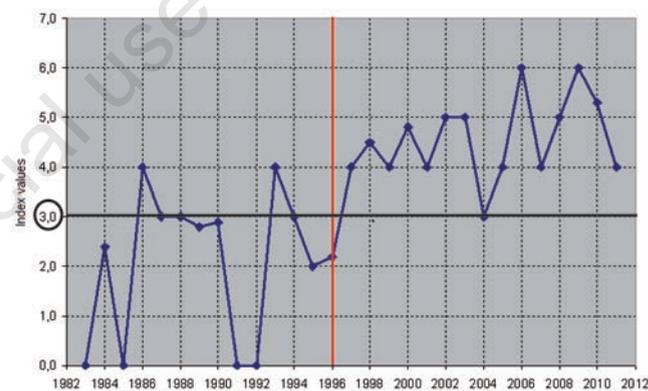


Figure 5. Index values corresponding to rainfall conditions for malaria diffusion from 1983 until 2011. The period after 1996 is for indices > 3 (identified by the red line).

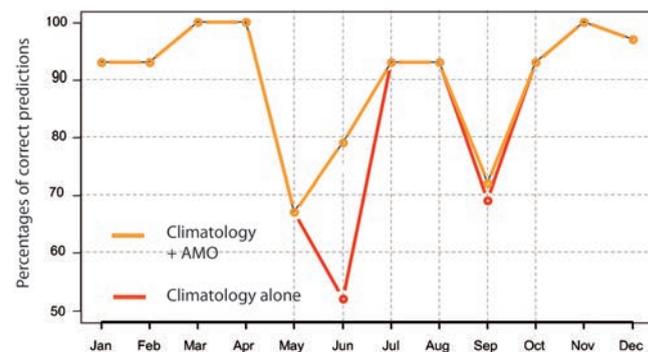


Figure 6. Monthly correct predictions (in %) obtained by using results got from climatology only (in red) and compared to modelled results which included the Atlantic Multi-decadal Oscillation phases (in orange). Differences are seen in June (26%) and September (3%). The predictions using the Atlantic Multi-decadal Oscillation phases are generally better.

study combining the AMO and the Tropical North Atlantic (TNA) which, according to Paeth *et al.* (2003) should be implemented since the two indices are linked with the ITCZ location and the rainfall amount (Balaji *et al.*, 1998).

Predictability of malaria risks

The 80-mm threshold of monthly total rainfall for favourable malaria conditions in the Nouna region was analysed according to Tanser *et al.* (2003) using three modelling techniques from Météo-France: use of rainfall climatology; rainfall as a function of the AMO phases; and logistical regression using the Météo-France's Arpege System 3 model.

Insofar as the precipitation index (INDp) is computed, 80 mm should be the minimum for one month along with two months of rainfall ≥ 60 mm.

Use of climatology

The monthly rainfall forecast for thresholds >80 mm was assessed by consulting the data for the Nouna region during the 1983-2011 period. It was found that four months (June-September) had a probability of ≥ 0.5 to reach this value and therefore defined as having an INDp=1. Thus, JAS were the only three months during the 1983-2011 period when the 80-mm threshold was attained. For the other months, the INDp=0 (not shown). The details for the monthly averaged correct probabilities (in %) from the model using the above prediction model can be seen in Figure 6 (red dots from the model compared to yellow dots for the actual data in the figure). Apart from June and September, the predictions from the model were quite good, confirming that the model was weak at estimating rainfall at the beginning and at the end of the rainy season. During June the threshold probability was <0.5 for unknown reason.

Use of climatology as a function of the Atlantic Multi-decadal Oscillation phase

The AMO is very important for modulating rainfall output in Nouna as shown by Vignolles *et al.* (2016). The period has been subdivided into a negative phase during the 1983-1995 period and a positive phase during the 1996-2011 period. The results for the >80 -mm threshold are presented in Figure 7. Comparing this AMO-positive phase with the AMO-negative phase (Figure 6), the probability percentage improved, particularly from May-June until September. The June forecast improved considerably (from 52% to 79%) when the AMO phases were taken into account, whilst the forecast for September was only slightly improved (from 69% to 76%). This means that the low-frequency modulation of monthly rainfall by the AMO phases somewhat compensates for the ability of the model to represent the beginning and the end of the rainy season each year.

Logistical regression using Arpege System 3 model

This relatively new approach (further information is available at http://www.wcrp-climate.org/WGNE/BlueBook/2008/individual-articles/06_Bouttier_Francois_080228contribNWP-MF_WGNE_2008.pdf) helps improving the prediction of the threshold limit of 80 mm per month (Bader *et al.*, 2006). This seasonal forecasting model from Météo-France is a numerical global coupled model using: Arpege v. 4 with a T63L91 grid for atmosphere modelling; OPA v. 8.2 (with the ORCA grid* of 2° at the surface) is for the ocean component; Oasis v .2.4 for the surface coupler developed by the French Centre of Basic and Applied research (Cerfacs), which specialises in modelling and numerical simulation. The ORCA grid is a non-uniform grid. developed at Cerfacs (courtesy of C. Cassou) in Toulouse (http://www.cerfacs.fr/oa4web/papers_oasis/PRISM_OASIS_AC

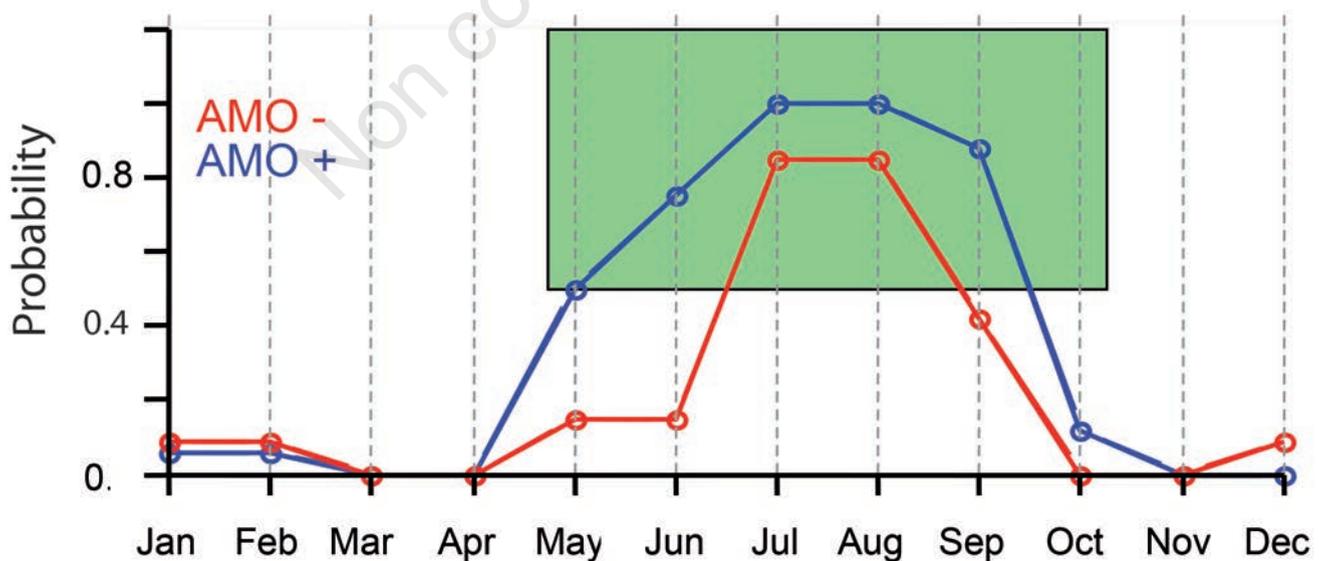


Figure 7. Monthly probability for having more than 80 mm of rainfall in Nouna, as function of the Atlantic Multi-decadal Oscillation (AMO) phases, is displayed: the blue/red curve is for positive/negative AMO. If the probability is less/more than 0.5 the rainfall threshold is less/more than 80 mm, a necessary condition for malaria diffusion. The green rectangle highlights the periods when the differences in probability between AMO phases are the largest.

CESS.pdf <https://www.ncl.ucar.edu/Applications/orca.shtml>).

This operational version provides post-2007 ensembles of 41 members with different initial conditions covering a 7-month post-initialisation period with daily increase (the first month functions as the relaxation month and is not used for forecasting). The initial conditions for the atmosphere are from ERA-40 (<http://www.cgd.ucar.edu/cas/catalog/reanalysis/ecmwf/era40/index.html>), whilst the operational model uses atmospheric initial conditions from the ECMWF analyses.

Instead of predicting the accumulated amount of rainfall and the limit given by the threshold (above or below), a logistic regression was used. To estimate the prediction over the threshold, six different models were tested: Model 1: over threshold ~ Simulation + AMO months; Model 2: over threshold ~ Simulation + AMO + NAO months; Model 3: over threshold ~ Simulation + NAO months; Model 4: over threshold ~ Simulation + AMO and NAO phases; Model 5: over threshold ~ Simulation NAO phases; Model 6: over threshold ~ Simulation AMO phases.

Simulation is the Arpege system 3 prediction based on the AMO index (<http://www.esrl.noaa.gov/psd/data/correlation/amon.us.data>; Enfield *et al.*, 2001), the NOAA CPC NAO index (<http://www.esrl.noaa.gov/psd/data/correlation/nao.data>), monthly values and a ranking factor depending on the month.

A 6-month lag was used with the AMO and NAO indices which is the optimum lag in terms of correlations with rainfall amount. AMO and NAO fluctuations were added to the regression models since they were not represented by Arpege System 3. According to the Mercator-analysis for the 1979-2007 period (Ferry *et al.*, 2007), the experimental referral is 11 members for a *posteriori* forecast (hindcast) covering 29 years. The model was initialised in March-03 (prediction for May to September); April-04 (for May to October); May-05 (for June to October); and June-06 (for July to October), following the way the simulations were implemented (Table 2).

Whilst the horizontal grid-points were 2.5° apart in the Nouna region, monthly averages were computed to obtain a single rainfall time-series for the region, for the 1983-2011 period and for the above four initialisations. Once again, a deterministic approach was implemented: 11 members from the referral experiment (1983-2007) and the 41 members obtained from running the operational model (2007-2011). The logistical regression was used here to directly predict the rainfall threshold and/or above the threshold. Six regression models were thus tested.

The performance of the proposed predicting system was compared with the other two predictive methods, i.e. climatology alone and climatology following the AMO phases. The same periods were used from the climatology and the four initialisations periods. Then receiver operating characteristics (ROC) curves (Figure 8) and their values (Table 3) were computed following the example set by Mason and Graham (2006).

Table 3 shows the different ROCs that were calculated for each model (Figure 8) and each initialisation and according to the results from the ROC analysis (Figure 8, dashed curves). A ROC area is equivalent to the Mann and Whitney U-statistic (1947) which tests the significance of forecast event probabilities for cases when events actually occur compared with cases when events do not occur. Thus, an area of 1 represents a perfect test, while an area of 0.5 is not useful, which in our case means that the best predicting approach is the one using climatology combined with the AMO phases (climate+AMO) for all cases with different initialisations. It can be deduced that the overall performance from

Table 2. The deterministic approach displayed.

Initialisation dates	Deterministic time series
March 2003	May to September 1983, ..., May to September 2011
April 2004	May to October 1983, ..., May to October 2011
May 2005	June to October 1983, ..., June to October 2011
June 2005	July to October 1983, ..., July to October 2011

Eleven members obtained from the referral experiment (1983-2007) and 41 members from running the operational model (2007-2011). Monthly averages were computed to obtain a single rainfall time-series for the 1983-2011 period and for the above four initialisations.

Table 3. Outcomes for the different models and simulations with acceptable receiver operating characteristic values.

Simulation model	3	4	5	6
Climate+AMO	0.86	0.90	0.92	0.94
Climate	0.80	0.86	0.87	0.89
Simulations+AMO+month*	0.78	0.85	0.86	0.87
Simulations+AMO+NAO+month*	0.77	0.84	0.86	0.87
Simulations+NAO+month*	0.74	0.81	0.85	0.84
Simulations+AMO+NAO	0.80	0.84	0.88	0.88
Simulations+NAO	0.78	0.83	0.86	0.86

AMO, Atlantic Multi-decadal Oscillation; NAO, North Atlantic Oscillation. *Different leading initialisation months. Values around 0.5 are not counted as useful, while figures close to 1 are deemed to be very good. Maximum values (bold) were found for the Climate+AMO simulations.

models using Arpege System 3 is somewhat better than those using climatology including AMO phases instead of climatology alone (black curves).

Conclusions

Based on the available data from 1983 until 2011, this study shows that the important parameter for malaria risks is not only rainfall but also the monthly total rainfall with a 80-mm threshold for one month in a given 3-month sequence. Prediction of accumulated rainfall >80 mm in the Nouna region shows that it would be preferable to use a model combining climatology with the AMO phases. Knowledge of these phases and its low-frequency variability is thus very important for the regional Health Information Systems (HIS) and should be included in adapted control strategies.

The logistical regression for the 1983-2007-reference period based on Arpege System 3 utilised the ERA40 reanalysis for atmospheric initial conditions, whilst the operational model was based on the ECMWF conditions. By separating the two periods it was found that 75% of the forecasts based on the six models were correct before 2007 increasing to 80% afterwards. This result is somewhat surprising and not very encouraging for models predicting seasonal variability. Future testing of a more sophisticated method, such as filtering the Nouna data by using EOFs prior to analyses, would be useful.

During the historical period of study following Craig's model, the conditions deemed favourable and those deemed unfavourable for malaria, were essentially controlled by rainfall, which are under the influences of the AMO phases. Temperature conditions

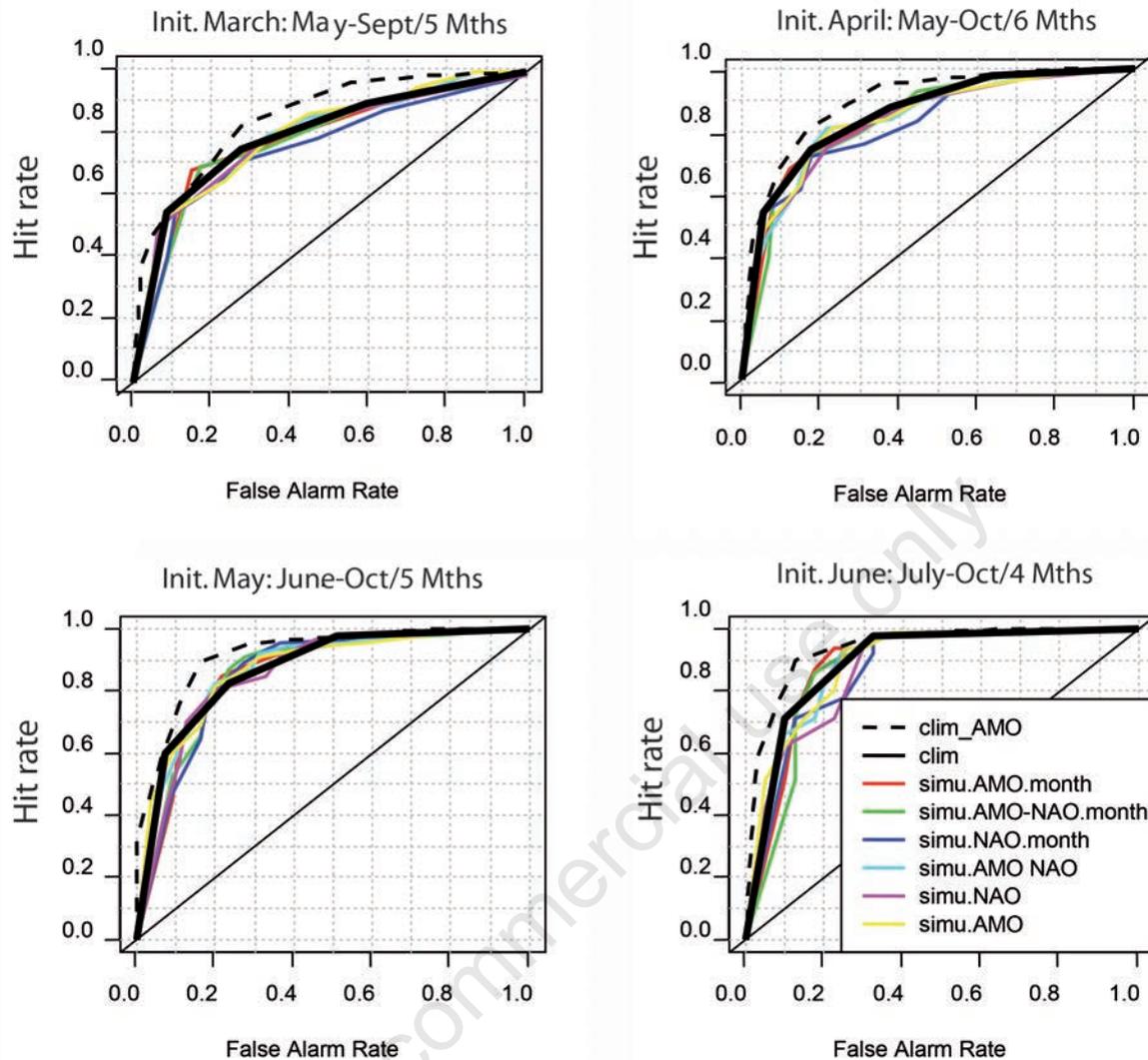


Figure 8. Eight relative operating characteristics or receiver operating characteristic curves for climatology and Atlantic Multi-decadal Oscillation phases, and the other six modelling predictive approaches, and for different initialising months. Ordinate is for hit rates, abscissa is for false rate.

were also favourable during the rainy seasons. According to the climate projections for the 21st century, and preliminary results from models used for the Coordinated Regional Climate Downscaling Experiment (CORDEX) (<http://cordex.org>), environmental conditions should change, particularly insofar as temperature is concerned. A follow-up research is recommended to see if a large temperature increase in the Nouna region would become a limiting factor, other parameters being equal, thus leading to a reduction of malaria risk during the 21st century.

References

- Bader J-C, Piedelievre JP, Lamagat J-P, 2006. Seasonal forecasting of the flood volume of the Senegal River, based on results of the ARPEGE Climate model. *Hydrol Sci J* 51:406-17.
- Balaji R, Kushnir Y, Tourre YM, 1998. Observed decadal midlatitude and tropical Atlantic climate variability. *Geophys Res Lett* 25:3967-70.
- Bjerknes J, 1964. Atlantic air-sea interaction. *Adv Geophys* 10:1-82.
- Craig MH, Snow RW, le Sueur D, 1999. A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitol Today* 15:105-11.
- Enfield DB, Mestas-Nunez AM, Trimble PJ, 2001. The Atlantic Multidecadal Oscillation and its relationship to rainfall and river flows in the continental U.S. *Geophys Res Lett* 28:2077-80.
- Ermert V, Fink AH, Jones AE, Morse AP, 2011. Development of a new version of the Liverpool Malaria Model. I. Refining the parameter settings and mathematical formulation of basic processes based on a literature review. *Malaria J* 10:35.
- Ferry N, Remy E, Brasseur P, Maes C, 2007. The Mercator global ocean operational analysis system: Assessment and validation of an 11-year reanalysis. *J Mar Syst* 65:540-60.
- Knight JR, Robert J, Allan RJ, Chris K, Folland CK, Vellinga M, Mann ME, 2005. A signature of persistent natural thermohaline circulation cycles in observed climate. *Geophys Res Lett*



- 32:L20708.
- Mann HB, Whitney DR, 1947. On a test of whether one of two random variables is stochastically larger than the other. *Ann Math Stat* 18:50-60.
- Marechal F, Ribeiro N, Lafaye M, Guell A, 2008. Satellite imaging and vector-borne diseases: the approach of the French National Space Agency (CNES). *Geospat Health* 3:1-5.
- Mason SJ, Graham NE, 2006. Areas beneath the relative operating characteristics (ROC) and relative operating levels (ROL) curves: Statistical significance and interpretation. *Quart J Roy Met Soc* 128:584.
- Paeth, M, Latif M, Hense A, 2003. Global SST influence on twentieth century NAO variability. *Clim Dyn* 21:63-75.
- Paz S, Tourre YM, Brolley J, 2008. Multitemporal climate variability over the Atlantic Ocean and Eurasia: linkages with Mediterranean and West African climate. *Atmos Sci Lett* 9:196-201.
- Tanser FC, Sharp B, le Sueur D, 2003. Potential effect of climate change on malaria transmission in Africa. *Lancet* 362:1792-8.
- Tourre YM, Balaji R, Kushnir Y, 1999. Dominant patterns of climate variability in the Atlantic Ocean during the last 136 years. *J Clim* 12:2285-99.
- Vignolles C, Lacaux J-P, Tourre YM, Bigeard G, Ndione J-A, Lafaye M, 2009. Rift Valley Fever (RVF) in a zone potentially occupied by *Aedes vexans* in Senegal: Dynamics, mapping and risks. *Geospat Health* 3:210-20.
- Zhang R, Delworth TL, 2006. Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes. *Geophys Res Lett* 33:L17712.

Non commercial use only