The Drying Out of Soil Moisture following Rainfall in a Numerical Weather Prediction Model and Implications for Malaria Prediction in West Africa

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ABSTRACT

This paper investigates the response of the land surface and the lowest section of the atmospheric surface layer to rainfall events and through the subsequent drying out period. The impacts of these sequences of rainfall and drying events in controlling near-surface temperatures are put into the context of malaria transmission modeling using temperature controls on the survivability of mosquitoes that are developing the malaria parasite. Observations using measurements from a dwelling hut, constructed to a local design at Wankama near Niamey, Niger, show that as the atmosphere gets moister and colder following rainfall, there is a potentially higher risk of malaria transmission during the rainy days. As the atmosphere gets warmer and drier during the drying period, there is a potentially decreasing rate of malaria transmission as the increasing temperature reduces the survivability of the mosquitoes. A numerical weather prediction model comparison shows that the high-resolution limited-area model outperforms the global-scale model and shows good agreement with the observations. Statistical analysis from the model results confirms that the findings are not restricted to a single location or single time of the day. It was also found that air temperatures over forest areas do not change as much during the study period, since the longer memory of the soil moisture means there is relatively little influence from single rainfall events.

1. Introduction

This paper investigates the atmospheric surface layer response to the frequency of rainfall events and the subsequent drying out of the land surface. It will show that the frequency of rainfall events is important for keeping temperatures within a critical range for the survivability of mosquitoes and thus influences the transmission of malaria. The notion of coupling between evaporation and precipitation (e.g., Mintz and Serafini 1992) has been developed to show that a positive feedback from the recirculation of precipitation through the soil moisture reservoir may lead to prolonged persistence of anomalous wet or dry spells (Betts et al. 1996; Taylor and Lebel 1998). Understanding the role of the feedback cycle between soil moisture, surface evaporation, and precipitation on continental scales has been featured in all of the Intergovernmental Panel on Climate Change (IPCC) reports, including the most recent (Fourth Assessment Report, AR4), along with the ability of GCMs to produce realistic monthly and seasonal-scale evolution patterns of these processes. West Africa has been found to be a hot spot with robust feedback signals in this soil–moisture–precipitation coupling in GCMs (Koster et al. 2004), and this robust coupling could offer the promise of improved seasonal climate predictions in this area (Notaro 2008; Wang et al. 2007).

To advance our understanding of the land surface–atmosphere feedback on or beyond seasonal scales, we...
need first to know the processes that govern the interactions on the shorter time scales of a few days and beyond. Satellite images reveal that the development of convective clouds in the Sahel is sensitive to wet surface soil moisture patches (Taylor and Ellis 2006). The mechanisms behind their formation are mesoscale gradients in land surface properties; for example, soil moisture from recent rainfall can induce circulations in the atmosphere, which could lead to subsequent rainfall (Taylor et al. 2003, 2007). The linkage between the soil moisture record of a prior rain event and subsequent future rainfall events may imply the possibility to improve local weather prediction through the examination and incorporation of feedback mechanisms in NWP models.

The interactions between the land surface and atmosphere are still not well tested in numerical weather prediction (NWP) models, as the model needs to resolve the coupling between the cloud fields, the surface radiation budget, soil moisture and surface evaporation, and other processes (see, e.g., Eltahir 1998). Wallace and Holwill (1997) have indicated that in the vicinity of Niamey most of the evaporation occurs during the first day directly after rain. Currently, it is not realistic to ask the operational NWP models to represent this type of feedback in terms of precipitation forecasting in West Africa as the diurnal variation of the atmospheric boundary layer in this area is complex (Parker et al. 2005). However, it is important to investigate how the diurnal cycle of temperature and humidity before and after rainfall is captured by a numerical model. It is also important to investigate the degree to which the representation of this diurnal cycle is important for models of impacts, for example, malaria transmission, which is sensitive to temperature and humidity (Morse et al. 2005).

Malaria transmission occurs in areas where environmental conditions are suitable for both the parasite and the vector. Therefore, seasonal climate forecasts that have an adequate simulation of interannual variability in the seasonal cycle could be used for malaria prediction (Morse et al. 2005). Conversely, the application of seasonal climate forecasts in malaria prediction could act as an evaluation for the climate forecast itself (Morse et al. 2005); hence, the application of NWP output in a malaria prediction context discussed in this paper could be potentially useful for the evaluation of weather forecasts as well. Temperature drives the development of the parasite within the vector and it also drives the developmental life cycle of the vector. For both developmental cycles, there are minimum and maximum temperature thresholds and, within bounds, higher temperatures lead to greater rates of development. Figure 1 illustrates the different risk levels of an infected mosquito surviving to become infectious depending on temperature (Jones 2007). A temperature between 23° and 27°C provides the optimum thermal environment for malaria transmission according to some modeling studies. Precipitation is important in providing breeding sites for mosquitoes and for increasing the humidity of the air, which increases the survival of the vectors.

As a first attempt, this paper aims to investigate how NWP model surface-layer fields develop during the drying-out period between rainfall events, and the implications of the modeled changes for malaria development as the atmospheric temperature and moisture vary. One special case (26–29 July 2006) is chosen, as it rains on the first and last days while on the whole keeping dry in most of West Africa (see detailed description in section 2) between the two rain events. Both observations and a model simulation are used in this study, and they will be briefly introduced in section 3. We will focus on the Niamey site in section 4 to examine the model performance at a single grid point and then extend the analysis to the whole model domain in order to undertake statistical analysis in section 5. A further investigation of the impact of surface characteristics is how section 6. Section 7 conducts a discussion and summary. The variations in daily rainfall during the four case study days provide an excellent opportunity to investigate how the atmosphere dries out following rainfall events and then reacts to the new rainfall events.

2. Case study introduction

The case study period from 26 to 29 July 2006 provides a platform to study the drying-out period between rainfall events. Figure 2 illustrates the daily rainfall amounts...
with 3-hourly satellite rainfall estimation using the National Oceanic and Atmospheric Administration/Climate Prediction Center (NOAA/CPC) Morphing Technique (CMORPH; information online at http://www.cpc.ncep.noaa.gov/products/janowiak/cmorph_description.html). A rain belt is observed on 26 July, ranging from the coastal area in Guinea to northern Nigeria with a pronounced rainfall center in southeast Mali, western Niger, Burkina Faso, and northern Benin. This rainfall pattern is associated with a large-scale circulation driven by an African easterly wave (AEW; see Janicot et al. 2008 for a review). Triggered by the passage of the synoptic wave, the majority of the rain moves westward to the coastal region on 27 July, leaving the central continental area dry with only a few small rain patches near Niamey. The heavy rain moves away from the continent on 28 July. There are convective systems initializing in the border between Nigeria and Cameroon on 27 July, which develop slowly and move westward. On 30 July, almost the entire southern part of West Africa near the coast is wet, with heavy rain over Ghana and Benin.

3. Observational datasets and model

Surface temperature and rainfall at Niamey (13.48°N, 2.17°E) are derived from Meteorological Interactive Data Access System (MIDAS) Land Surface Observation Station Data, which are available from the British Atmospheric Data Centre (BADC; information online at http://www.badc.ac.uk). The data are collected every 6 h and the station is located at the airport in Niamey. Uniquely in this project, the microclimate conditions within the roof space of a traditionally constructed woven grass hut were monitored. It is within this microclimatic space that mosquitoes that have taken a human blood meal and have potentially ingested malaria parasites, develop the next stage in the parasite’s life cycle. The microclimate also controls the proportion of the mosquitoes that survive, long enough, to become infectious and thus become able to transmit the disease. This hut was constructed by local villagers and is in Wankama (13.65°N, 2.65°E). Although the hut was not inhabited, and therefore does not exactly replicate the environments in which malaria-transmitting mosquitoes dwell, it
enables us to make a first attempt at quantifying the departure of the true mosquito microclimates from the climatic values obtained from the routine observing and modeling systems.

Temperature and relative humidity were automatically monitored inside and outside the hut every 10 min. The hut site has been recording microclimate information for more than 2 yr (since May 2006) and has archived an extremely valuable dataset at an interseasonal temporal scale for malaria studies, which will be presented in a forthcoming paper. This dataset, part of which is presented in this paper for the case studies, allows for comparison between an approximation of the climate space experienced by the mosquitoes in their natural resting environment and the simulated surface climate from the Unified Model.

The latest version of the New Dynamics Unified Model version 6.1 (UM6.1) developed at the Met Office was used both for the global scale (horizontal resolution of 40 km) and for a limited scale (horizontal resolution of 12 km; referred to as LAM hereafter). The model is initialized from the European Centre for Medium-Range Weather Forecasts (ECMWF) dump file, which is the assimilated ECMWF operational analysis, giving a snapshot of the UM in a file format that can be used to start the GCM from any set starting point without the need to spin up the model, and the LAM run is nudged with the global model output at lateral boundaries once an hour (domain shown in Fig. 3). The LAM run is integrated continuously from 0000 UTC 26 July through 0000 UTC 29 July, without restart, to achieve an integrated run of the model for the 4 days without break, while the global run is restarted every 24 h, to simulate as close to real weather conditions as possible. Detailed information about the model can be found on the Met Office UM Web site (http://www.metoffice.gov.uk/research/nwp/numerical/unified_model/). As our approach to analyzing the model results does not concern one specific parameterization or process but instead the general model performance, we exclude a detailed description of model parameterization in this paper.

4. Results at the Niamey site

Figure 4 shows the increase of surface temperature after the rain that fell in the early morning on 26 July. Over a 3-day period, the daily maximum temperature goes up to 36°C from 30°C and the minimum temperature goes up to 27°C from 23°C. The two small rainfall events recorded by the MIDAS data during the evening of 27 July and the early morning of 28 July do not hold back the increase in the temperature, while the temperature drops marginally on 29 July, despite there being no rainfall recorded. Although the data provide useful cross-validation information for our hut data, they are only available at 6-h intervals, which prohibit detailed examination of the diurnal variations important to a thorough microclimate study. Many impact models, including many malaria models, take a derived daily mean temperature; however, other impact modeling systems can have more frequent time steps. In both cases it is important that the diurnal cycle simulated by the model is close to that observed on the ground as often the model archive’s mean temperature is calculated as
a mean of the temperature at the four synoptic hours. A model whose temperature cycle significantly leads or lags the observations would cause problems in the calculation of a mean temperature. The same issues also arise with the diurnal humidity cycle.

Figure 5 illustrates the variations in temperature and relative humidity data observed from inside the hut. Figure 5 also shows the general increase of the temperature, as in the MIDAS data shown in Fig. 4. As the hut records every 10 min, it reveals more detailed features of the variation. The humidity varies at similar phases to the temperature. The rapid temperature drop and humidity increase correspond to the passage of a major mesoscale convective system that passes through the area. We assume that rainfall happens when convective systems pass at midday on 26 July and at midnight on 27 and 28 July, as there is no rain gauge on the hut site. The speed of the changes is another indication of a significant convective system. After the heavy rainfall near midday on 26 July the temperature stays at around 27°C through the early morning on 27 July and, correspondingly, the air is humid as well during this period. The subsequent warming that follows over the next few days agrees with the diurnal temperature cycle found by Wallace and Holwill (1997), who showed, while working in Niger, that evaporation rates were only at the potential evaporation rate the day after rain, dropping away rapidly in subsequent days. In general, the daily variation of humidity agrees with the hut observations but misses the observed rapid changes related to localized rainfall events.

Figure 2 shows a similar plot to that in Fig. 6 but for 1-h output from the LAM run. The patterns of temperature and humidity are similar between the global model and LAM runs, except that LAM results, with a higher temporal frequency of data points, show the rapid changes due to rainfall events. Compared to hut observations, the model gets drier in the evening, especially in the LAM. The global and LAM runs are raining at different times.
except near midday on 26 July and around midday on 28 July. The rains in the LAM run agree with the hut observations in the late evening on 27 and 28 July, but the LAM still misses the heavy rain on 26 July in the afternoon that was observed in Niamey in Fig. 4. The differences in the rainfall between the two model runs are partly due to the fact that the LAM run is integrated for the whole period and is only nudged at lateral boundaries by the global model output, which, however, restarts every 24 h. The modeling system was run in this configuration to give the best GCM output possible, whereas the LAM was allowed to run freely, being just nudged at its lateral boundaries by the GCM output.

To conclude the analyses at Niamey, the observations show that the atmosphere gets wetter and colder following the rainfall and then becomes warmer and drier as the surface dries, as is to be expected. On the daily time scale, after a rainy day the initially cool and moist atmosphere gets gradually warmer and drier until the next rainy day. Both the global and limited area models show they can represent the warming and drying trends on a daily basis. The LAM outperforms the global model with regard to the diurnal cycle, due to its better representation of the rainfall at this single observation location, and could better resolve the passage of the convective systems, although many differences exist between the LAM and the hut observations in terms of strength and duration of the convective systems. We need to bear in mind that the above discussion is based on the comparison between one model grid point and one station for one case study. More stations and longer time series are encouraged in future studies. In the next section, we look for rainfall cases with more than 1 day of drying in the model simulation, benefiting from the spatial coverage of the entire LAM domain.

5. Statistical analysis

The LAM shows similar feedback patterns between rainfall, temperature, and humidity, as does the global model run. However, the LAM results show better agreement with the observations; therefore, the following analysis focuses on the LAM runs. First, we select the model grid points according to the following rules: 1) the daily rainfall amount is larger than 5 mm day\(^{-1}\) on 26 and 29 July and 2) the daily rainfall is less than 5 mm day\(^{-1}\) between the rainy days. The locations of the points are shown in Fig. 2, extending from Liberia on the coast to continental regions like southern Mali and western Burkina Faso. As shown in Fig. 7, Niamey is not included in the data points. To better intercompare the atmospheric conditions among the 4 days, we select model data at 1200 and 1800 UTC, respectively, in order to avoid the influences of diurnal variations. To link with the impacts on developing malaria parasites in our hypothetical infected mosquito, we set the temperature histogram bins to 20°, 22°, 23°, 27°, and 30°C according to Fig. 1 and the humidity to 30, 50, 70, 80, and 90% (see also Hoshen and Morse 2004).

Figure 8 shows the percentage of grid points at 1200 UTC on the four different days for a series of temperature and humidity categories. On the first rainy day (26 July), 70% of the temperatures are distributed between 23° and 27°C, which is the ideal temperature range for mosquitoes to develop malaria parasites and to survive long enough to transmit the disease. Furthermore, it is also very moist, with 70% of the points having a relative humidity that is higher than 80%. During the dry days (27 and 28 July), the temperature increases considerably and the air becomes much drier. On the second dry day there is a larger change in the conditions than there was on the first dry day, both in the temperature and humidity fields. On the second rainy day (day 4 in the sequence, 29 July), the temperature and humidity move back to the pattern of the first rainy day, with a large positive tail;

![Figure 6: Variations of surface temperature, rainfall (column bar), and relative humidity at Niamey between 26 and 29 Jul 2006, derived for Niamey from the nearest grid cell in the UM global simulation at 0–24-h forecast time.](image)

![Figure 7: As in Fig. 6, but from a LAM run at 1-hourly intervals.](image)
some grid points remain relatively hot even though it rained, leading to a “memory” of the dry periods. This implies that the longer the break cycle, the less favorable it becomes to developing infected mosquitoes; this may be inferred from Fig. 1, which shows that above 30°C the number of mosquitoes surviving to become infectious is half of that at the optimal temperature. However, there are around 17%–19% of grid points in the temperature field staying in the 23°C–27°C range all the time. We suspect that this relates to some specific surface conditions, for example, forest, which has much longer memory than the few days we discuss here. This surface influence will be confirmed further in the next section.

Figure 9 shows plot that is similar to Fig. 8 but at 1800 UTC. In general, the variations in the late afternoon are similar to those at 1200 UTC. On the first rainy day, more grid points in the domain are in the 23°C–27°C range. During the dry period (the second and third days), fewer points are left in this range. The air is moister in the afternoon than near midday during the 4 days. We also performed a similar study on other hours (figures not shown) and found similar responses, except for the different diurnal characteristics at different times of the day. We can conclude that the atmospheric conditions move to a warmer and drier state after the rainfall events during the drying period before the next rainfall event. With respect to malaria impacts, rainy days in summer provide ideal conditions for the development of infectious mosquitoes, but this will drop on the second day if it is dry. The longer the dry period lasts, the lower the conditions for malaria transmission will be. How to extrapolate the findings across time scales from a few days’ weather forecast up to seasonal climate prediction is within the context of developing seamless forecasting systems a future scientific task and would involving running lower-resolution seasonal forecast models with and without similar soil moisture conditions for this case study.

6. Surface influence

To examine the role of vegetation in the surface–atmosphere feedback during the drying-out period, the
surface characteristics of the points used in Fig. 8a are analyzed. Table 1 lists the distribution of vegetation information from data points of dry days (27 and 28 July) in Fig. 8a, with each column in the vegetation characteristics table corresponding to the relevant bar in Fig. 8a. As the model does not explicitly set the type of surface vegetation, we must infer a type from the other vegetation characteristics. The grid points that stay in the 23–27°C temperature range on the dry days are the points with large vegetation fractions (0.87–0.95), large leaf area indexes (4.9–8.5), deep root depths (0.8–1.3 m), and high canopy heights (5.2–25.2 m), which we assign as mostly forest. The other locations staying within 27–30°C, 30–35°C, and 35°C are designated as shrubland or grassland because of their high vegetation fraction but relatively shallow root depth and canopy height. These findings show that the atmospheric response time (at least 2 days) above forested areas is much longer than those above other surface types. This means that in the forest area the atmosphere does not react to the rainfall events as fast (~2 days at least) as other areas during the drying-out period, as the memory of soil moisture in a forecast is much longer than a few days.

Table 1 shows the role of forested areas in maintaining surface temperatures at threshold that are more favorable for malaria transmission. However, caution needs to be taken with the last statement as we do not know the local topography or soil types that may favor the growth and preservation of forest. But targeting malaria eradication campaigns in relatively hot and arid zones within areas that have remaining forest may be beneficial. Further, Table 1 shows that the inclusion of realistic vegetation information in future higher-resolution seasonal forecast runs will be beneficial for impact modeling communities who model biological processes that have limiting thresholds (e.g., malaria transmission).

### Table 1. Vegetation characteristics of points shown in Fig. 8a grouped by the surface temperature ranges on 27 and 28 July.

<table>
<thead>
<tr>
<th>Surface temp range (°C)</th>
<th>Vegetation fraction</th>
<th>Leaf area index</th>
<th>Root depth (m)</th>
<th>Canopy height (m)</th>
<th>Possible surface type</th>
</tr>
</thead>
<tbody>
<tr>
<td>23–27</td>
<td>0.87–0.95</td>
<td>4.9–8.5</td>
<td>0.8–1.3</td>
<td>5.2–25.2</td>
<td>Mostly forest</td>
</tr>
<tr>
<td>27–30</td>
<td>0.90–0.95</td>
<td>3.7–5.0</td>
<td>0.6–0.8</td>
<td>0.2–6.0</td>
<td>Intensive shrubland/grassland</td>
</tr>
<tr>
<td>30–35</td>
<td>0.84–0.95 (with a thin tail down to 0.3)</td>
<td>3–5 (with several points up to 6)</td>
<td>0.55–0.8 (with a thin tail down to 0.25)</td>
<td>0.2–6.0</td>
<td>Shrubland/grassland</td>
</tr>
</tbody>
</table>

7. Conclusions

This paper studies the atmospheric reaction to wet surfaces that result from rainfall events and how the atmosphere develops on a daily time scale during the drying-out period before the next rainfall event. More importantly, we analyze the results from the perspective of conditions that might limit the predictive capability of dynamic malaria transmission models (Hoshen and Morse 2004) due to meteorological drivers. Surface observations, including measurements from a hut constructed to a local design at Wankama, reveal that the atmosphere gets wetter and colder immediately after rainfall events but makes a transition to warmer and drier conditions during the drying-out period before the next big rainfall event. One source of gridpoint output from the global and limited-area model UM shows some agreement with the observations, especially on a daily basis. A statistical analysis of LAM output concludes that the findings at Niamey are consistent with other points in the whole domain during summer. With respect to the ideal conditions for malaria transmission, the longer the dry period lasts, the lower the degree of the transmission risk.

As a first attempt at examining the utility of NWP forecasts in malaria predictability, this paper has highlighted the importance of the accurate representation of rainfall time scales. Many questions remain to be answered. While this paper suggests some conclusions on the basis of our single-station verification, and a more general statistical analysis of the model, a more extensive verification using more stations and longer analysis periods is needed. A longer study will also help the various applications sectors find the best location and time window to be analyzed, which could in turn improve the NWP forecasts of the area.

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