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METEOROLOGY

Potential to use seasonal climate forecasts to plan malaria intervention strategies in Africa

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Potential to use seasonal climate forecasts to plan malaria intervention strategies in Africa

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Despite a reduction in the number of cases of malaria over the past century, it remains a disease with a heavy health burden. The life cycles of the malaria parasite and its mosquito vector are affected by climate, principally temperature and rainfall. Thus, in addition to other factors such as land cover, human migration, malaria interventions and socio-economic conditions which can alter the local disease prevalence significantly, year-to-year fluctuations in climate can lead directly to variability in the intensity of malaria transmission. The period of the malaria parasite development in both host and vector results in a temperature-dependent lag of approximately one to two months between the onset of suitably wet conditions for vector proliferation and the appearance of malaria symptoms. Thus accurate real-time forecasts of temperature and rainfall conditions could provide useful information concerning malaria transmission if employed in Malaria Early Warning Systems (MEWS). Researchers across 13 European and African research institutes have worked together to integrate data from climate modelling and disease forecasting systems to predict the likelihood of a malaria epidemic.

In this article we analyse the potential of an integrated malaria prediction system by identifying regions and months for which climate variability directly translates into significant variability in malaria transmission. Local temperature anomalies are predictable from one to two months ahead, while reliable rainfall forecasts are only available in eastern and southern Africa one month ahead. Nevertheless, the inherent lag between the rainy seasons and the onset of malaria transmission results in there being potential predictability of malaria cases three to four months in advance. This would extend the early warning available from environmental monitoring by one to two months.

Predicting malaria transmission: why?

Weather forecasts could extend the advance warning of outbreaks provided by climate monitoring and supply them on a regional or even continental scale. One of the first attempts to show the potential for this use of climate forecasts dates back to 2006. A collaboration involving colleagues from ECMWF showed the potential for using seasonal forecasts from DEMETER (Development of a Multi-model Ensemble System for Seasonal to Interannual Climate Prediction) to drive a simple statistical model for malaria. This provided a prediction of the total number of malaria cases for Botswana (see *Thomson et al.*, 2005 for further details). The forecasts appeared to have skill up to six months ahead, perhaps facilitated by the higher predictability in this location compared with others due to strong teleconnections to ENSO (El Niño–Southern Oscillation). At that time no attempt was made to assess the potential predictability of an operational system at a pan-African scale. Note that the derivation of a statistical malaria model to predict cases is only possible if long, reliable and readily available health data records exist; this is not the case for many countries in Africa.

During the three years (2010–2013) of QWeCI (Quantifying Weather and Climate Impacts on health in developing countries), a project funded by the European Commission's Seventh Framework Research Programme, we have attempted to build a MEWS (*Thompkins & Guiseppe*, 2014). Given the noticeable advance in the quality of ECMWF's seasonal predictions, this time the long-range forecasts have been used to drive a dynamical malaria model (*Tompkins & Ermert*, 2013). This model attempts to represent the physics of the malaria transmission cycle explicitly, and allows it to be applied in countries where health data records are short or not available.

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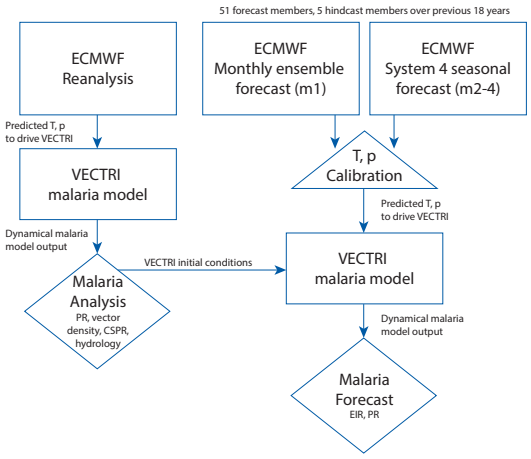
The first month of the forecast uses temperature and rainfall provided by the monthly extension of ECMWF's ensemble forecast. These are then substituted by data from the lower-resolution and longer-range seasonal forecasts from System 4 for months two to four (*Di Giuseppe et al.*, 2013). The integration of the VECTRI malaria model produces an ensemble of forecasts of a range of epidemiological and entomological parameters; the most useful parameters for operational applications being:

- *Parasite ratio* (PR): proportion of people infected.
- *Entomological inoculation rate* (EIR): the number of infective bites per person per time.

The malaria model is initialized from realistic initial conditions provided by a malaria analysis system obtained using forcing from the ERA-Interim reanalysis – see Box A.

Using this system we will try to answer two key questions: where in Africa would a MEWS providing regularly updated forecasts be most useful and what is the prediction skill of the malaria forecasts in these locations?

Schematic of the forecast system **A**



Schematic of the forecasting system set up, with boxes representing models, triangles for processes, and diamonds for products. The operational numerical weather prediction reanalysis of temperature (T) and precipitation (p) is used to drive the malaria model to provide a malaria analysis of epidemiological and entomological parameters (PR=parasite ratio, CSPR=Circumsporozoite Protein Rate), which are used as initial conditions for the forecast.

The malaria forecast uses climate information from the ensemble climate forecasts in the first month (m1), which is seamlessly combined with information from the seasonal forecasts in months two to four (m2-4). Both temperature and precipitation are calibrated before application to the malaria model, which then provides forecasts of PR and entomological inoculation rate (EIR).

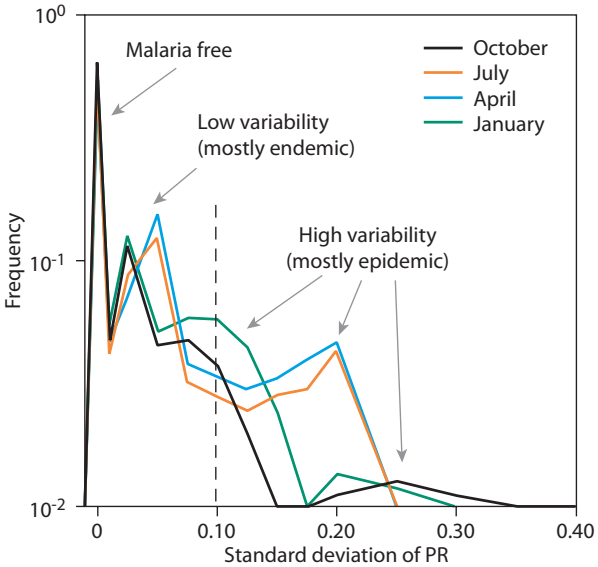


Figure 1 Probability density function of the standard deviation of the PR for four representative months of the year. The vertical dashed line represents a standard deviation of 10% used as a threshold in the analysis to identify high variability regions.

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Predicting malaria transmission: where and when?

Previous efforts to provide early warnings have pinpointed a selection of locations subject to sporadic epidemics or irregular short transmission seasons. In these locations adult immunity is lower and the intermittent transmission implies health facilities may not be adequately prepared for significant outbreaks. The first step is therefore to locate areas and calendar months with high variability in malaria prevalence, using the daily malaria analysis system.

The standard deviation of the parasite ratio for each calendar month provides an insight to the modes of variability of malaria transmission, with Figure 1 showing four example months. In each of these months the standard deviation of PR shows three distinct modes.

- ***Malaria free.*** There is a mode at zero parasite ratio which simply identifies malaria-free zones.
- ***Low variability.*** The second mode identifies regions where the year-to-year standard deviation is non-zero, but less than around 10%, with the upper bound changing slightly from month to month. This mode is associated with endemic zones, where transmission regularly occurs in those months each year.
- ***High variability.*** The third mode encompasses the remaining higher values of standard deviation exceeding 10%. The highest standard deviations belong to locations where transmission is very intermittent and does not occur every year but instead in occasional epidemic outbreaks.

Events in the high variability mode are termed as ‘true’ or ‘classic’ epidemic. However, this mode also includes locations where transmission is regular each year, but the transmission season is irregular in the particular month in question (e.g. occurring later or earlier according to variability in the onset of monsoon rains). Thus this mode also encompasses situations of ‘unusual seasonal transmission’ and may include mesoendemic and hyperendemic zones – see Box B for the definitions of mesoendemic and hyperendemic as well as hypoendemic and holoendemic.

Based on this analysis of the variability of malaria prevalence rates, we identified all locations where the standard deviation of PR for a particular month exceeds 10% of the population to identify the epidemic mode. In order to relate prevalence more closely to expected cases, an additional filter is applied to exclude months in which transmission intensity is minimal and no new cases are expected. This is accomplished by excluding months where the EIR falls below 0.01 per month. The locations are then subdivided into two categories.

- The first category includes the hypoendemic and mesoendemic zones where immunity is likely to be low and the malaria hazard impacts the entire population.
- The second category concerns the hyperendemic regions, where children under five are most at risk (most holoendemic locations are excluded by the PR variability threshold since the interannual variation is low for all months).

This subdivision is made since malaria interventions and preparations are likely to differ in the two transmission environments. The separation of hypoendemic/mesoendemic from hyperendemic regions is made using the common threshold of 0.5 for annual mean PR. This threshold can be applied to the whole population since the model neglects immunity, which increases parasite clearance rates in adults relative to malaria-naive children. However, it also implies that the model is likely to overestimate the hyperendemic region relative to the lower transmission classes.

Terms used to describe regional malaria risk **B**

The following terms have been used to empirically gauge regional risk.

- ***Hypoendemic.*** Little transmission, and the effects of malaria on the community are unimportant.
- ***Mesoendemic.*** Variable transmission that fluctuates with changes in one or many localconditions (e.g. weather or disturbance to the environment).
- ***Hyperendemic.*** Seasonally intense malaria transmission with disease in all age groups.
- ***Holoendemic.*** Perennial intense transmission with protective clinical immunity among adults.

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The map in Figure 2 identifies where and when a reliable malaria forecast would have a relatively high potential value to the decision maker. The map identifies epidemic regions such as the Sahel fringe, the East African highlands and the southern-most transmission regions skirting through Botswana, southern Africa and Mozambique. In each region the malaria model's representation of the vector and parasite life cycles results in a peak malaria transmission that is lagged with respect to the rainy season by one to two months. It is in these zones that the indication of an outbreak by a reliable forecast could trigger the whole host of intervention strategies, depending on the status of the national malaria control programme in question (control, elimination or post-elimination surveillance).

It is emphasized that the assessment of 'where and when' is only for the theoretical climate-related variability of malaria and may not reflect the situation in reality. If control measures have led to local eradication, for example, then indication of heightened hazard due to climate anomalies may serve to tighten surveillance and response measures to imported cases in the region in question to prevent explosive growth of secondary cases. Likewise, this assessment obviously neglects zones prone to epidemics due to non-climate factors such as population movements and breakdowns of health services due to conflict or other socio-economic factors.

In addition to these epidemic zones, the map also reveals areas with annual seasonal transmission but where high variability is prevalent in certain months of the year, for example, in a band spanning the northern half of the Ivory Coast, Ghana, Togo and Benin in West Africa during April and May. Malaria transmission variability is highest in these regions during the rain season onset (also in April/May at these latitudes) and is associated with the interannual fluctuations of the monsoon cycle which are highly variable from year to year. In these hyperendemic zones, health services are likely to be geared up to dealing with regular malaria transmission, unless funding shortages or breakdown of health structures preclude this. However, a skilful forecast would still be useful for ensuring timely mobilization of indoor residual spraying (IRS) teams using insecticide to kill mosquitoes that spread malaria.

Our subsequent analysis uses these maps to exclude locations for each calendar month where climate is deemed less relevant for interannual variability of malaria transmission.

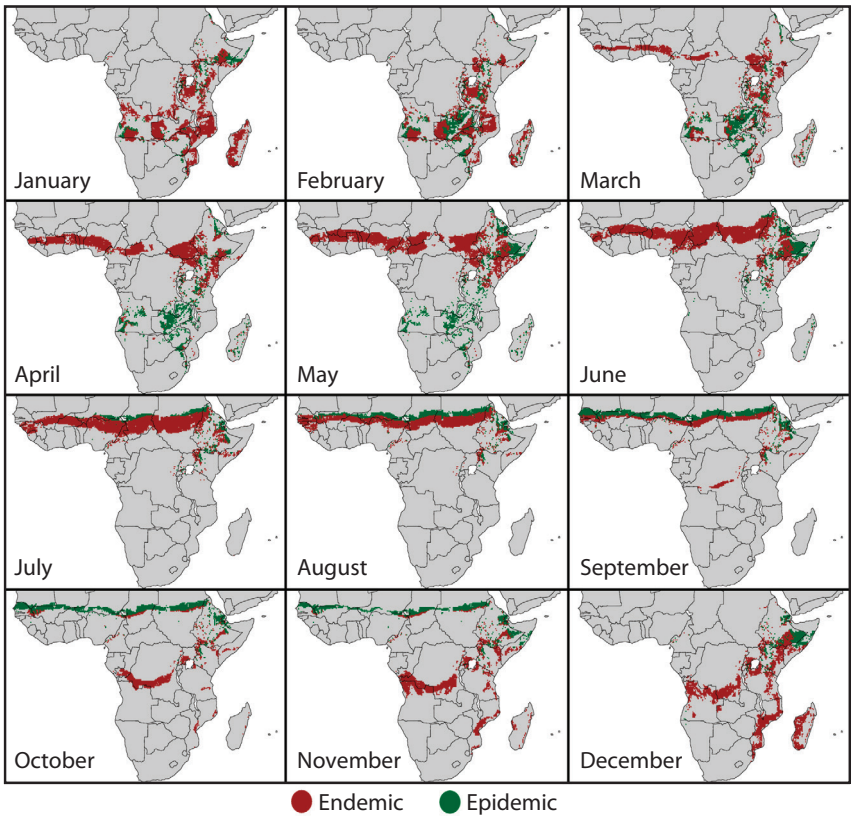

Figure 2 Locations of high variability in parasite prevalence are shown for each calendar month of the year, subdivided into endemic (hyperendemic and holoendemic, red) and epidemic (hypoendemic and mesoendemic, green) transmission zones.

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Predicting malaria transmission: how?

We now consider the potential malaria predictability in the locations that have been identified in Figure 2. Here the word 'potential' is emphasized as we use the malaria analysis system to quantify the malaria prediction skill. This is necessary as no continent-wide health data set exists. Thus the actual skill will be necessarily less than reported in this analysis due to the neglect of errors in the malaria modelling system. Nethertheless, the analysis should provide useful indicators to where skill deriving from climate prediction exists, and thus in which countries further national-level investigation of the system should be focussed.

The skill of the forecast is examined for both the climate and malaria forecasts using the operational forecasting system output for 2012. We analyze the forecasts of 2012, and the 18 years of hindcasts, giving an evaluation period of 1994 to 2012. Although ideally one would evaluate an ensemble system using probabilistic skill scores, the small ensemble size of the hindcast (five members) precludes this and thus an assessment is made for the skill of the ensemble mean anomaly correlation. Temperature and rainfall are validated against the ERA-Interim reanalyses. We identify the locations where skill in predicting malaria transmission is statistically significant one to four months in advance (referred to generically as 'malaria prediction skill') for each month. In addition to malaria, we show the skill in predicting anomalies of rainfall and temperature to identify which of these variables generate any identified malaria prediction skill.

Examining first the predictions one month in advance (Figure 3, first column), encouragingly, there is model skill in malaria predictions in the target prediction zones throughout the year. In some regions the predictability derives from correctly forecasting variations in temperature. However, in southern Africa, in a band stretching from Botswana through to Malawi and also across Eastern Africa, there are wide areas in which malaria predictive skill derives from both rainfall and temperature; for these the analysis does not show which variable contributes most to the skilful malaria prediction. In these regions rainfall predictability tends to be higher owing to stronger teleconnections with the El Niño phenomenon. Outside of these regions, skill in rainfall prediction appears limited in the areas of interest for malaria forecasting, in broad agreement with studies using the predecessor of the seasonal forecast (System 3).

In some locations the malaria forecasts are not significantly skilful, marked by a limited number of black points where predictions of all variables fail, or by blue, purple or red points which indicate skill in climate but not malaria prediction. In the northern-most Sahel belt spanning Senegal, Mali and Niger in July and August, wide areas display skill in temperature only (red colours) while in some places rainfall is also correctly predicted (purple colours) but no malaria prediction skill ensues. In this northern-most zone of the Sahel, rainfall variability and the northern extent of the monsoon limit malaria transmission. Thus, where rainfall predictions (despite bias correction) are inaccurate, a frequent shortcoming in atmospheric models, malaria predictions will also fail. Where both rainfall and temperature are skilfully predicted, the failure to translate this into accurate malaria prediction could relate to the non-linear relationship between transmission and rainfall, where intense rain events flush early-stage larvae breeding sites and monsoon breaks lead to puddle desiccation. This non-linearity is fully sampled by the high day-to-day variability of rainfall in the tropics, thus significant skill in predicting seasonal rainfall anomalies may not be sufficient if sub-seasonal rainfall variability is poorly represented.

Analyzing the malaria prediction skill for longer lead times of two to four months (Figure 3, columns 2 to 4), it is seen that the climate prediction system exhibits a sharp drop in skill at predicting rainfall and temperature two months in advance compared to one month. Despite this, there are wide areas for which the pilot MEWS still has significant skill for malaria prediction in months 2 and 3, and in smaller regions even four months ahead. This is due to the inherent lags between the rainfall anomalies and the resulting malaria transmission season. The skill in predicting malaria transmission in the second and third months derives from the climate information contained in the forecast initial conditions and the first more skilful month from the monthly forecast. This highlights the crucial role that the malaria analysis system has in correctly initializing the malaria modelling system. In areas where rainfall and temperatures are predictable beyond one month, such as in Eastern Africa, the malaria prediction advanced warning is extended beyond the three-month range.

The analysis indicates that, by driving the malaria model with long-range forecasts, useful information regarding the future transmission season in epidemic and seasonally variable endemic regions can be deliverable at least one, and in limited regions, two to three months earlier than would otherwise be the case using climate observations, which themselves provide more advance warning than the direct monitoring of symptomatic malaria cases.

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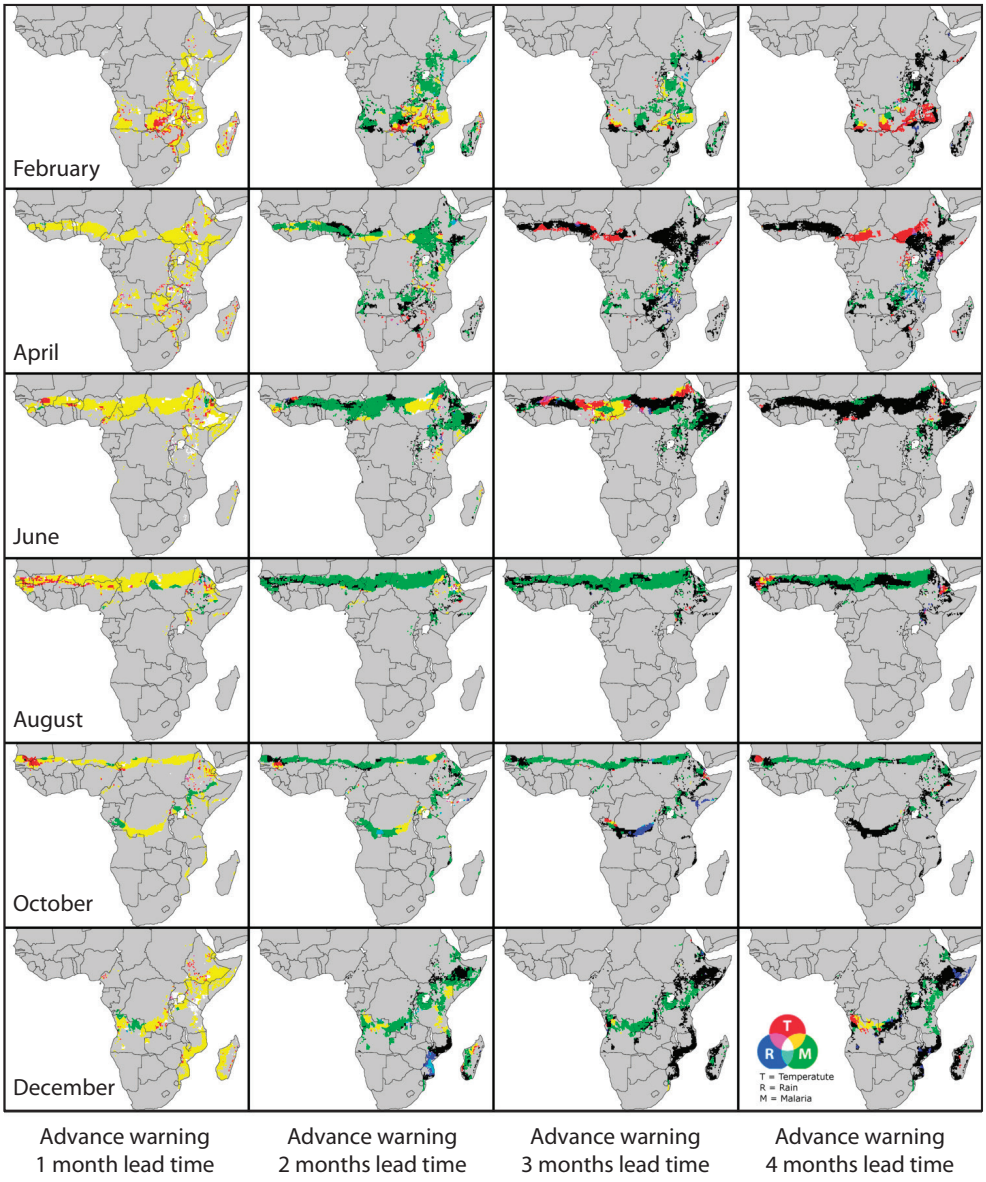

Figure 3 Composite plot of temperature (red), rainfall (blue) and malaria (green) forecast anomaly correlation coefficients that are statistically skilful at the 95% confidence level for issuing warnings for 1 through 4 months in advance (lead time) for alternate months of the year. White points mark cells with skill in all three variables, black points mark cells without any skill. See legend for colour definitions of intersecting categories.

From potential predictability to decision support: the next steps

The results we obtained have demonstrated the potential for skilful malaria predictions up to four months in advance over wide areas that were identified as having highly variable transmission for specific months. This is an important result; it demonstrates for the first time that climate forecasts may usefully extend the early warning available from environmental monitoring on a continental scale and reaffirms the potential importance of accurate climate information on this continent. However, it is important to emphasize that this study is just the first step because it is limited to identifying the potential skill in such a system.

The next phase is underway, in collaboration with two health ministries in Africa; this involves conducting a detailed evaluation of the system at the health district level. Such endeavours are complicated by the relatively short and often incomplete records of malaria cases available in most countries, which are infrequently confirmed by laboratory tests; this highlights the need for improved clinical datasets for the evaluation of MEWS required for their uptake. This interactive process will likely identify areas of the malaria modelling system in need of further development.

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In addition, the next phase will tackle the issues associated with integrating such forecast information into the present decision-making process. This will provide guidance on forecast products most useful at a district and national level, and how to best communicate forecast uncertainty to decision makers to effectively complement existing planning strategy.

As cited earlier, there is wide evidence that climate information could increase advance warnings and the cost-effectiveness of malaria interventions. However, demonstrations of MEWS based on climate monitoring have not been widely adopted in an operational environment to assist planning in African health ministries. To a large extent these ministries base decisions concerning drug distribution and interventions on long-term maps of mean malaria prevalence. In the past, health ministries have aimed to increase the efficiency of disease monitoring systems, improve the reaction time to the onset of epidemics and ensure coping strategies are sufficient with minimum cost. They have nevertheless been unfamiliar with the operational paradigm of using climate or other information sources to predict outbreaks in advance. Using climate information to predict outbreaks implies the incorporation of uncertainty into the decision-making process and the risk of costs associated with a prediction failure (termed a 'forecast miss'). The potential benefits of such information may be deemed to be outweighed by the perceived risk of an incorrect action.

The above considerations serve to emphasize that integrating climate forecast information into the decision-making process will require extensive country-level evaluation of the system's past performance, including cost–loss analysis of potential intervention actions taken on the basis of the information. To carry out such an analysis adequately, improvements in the representation of model uncertainty and increased ensemble sizes will be necessary, since the present system uses a single weather ensemble forecast to drive a single malaria model. Additional climate forecasting systems and malaria models should improve the representation of model uncertainty.

A further complication is that appropriate actions based on forecast information will also depend on a country's malaria intervention phase (malaria control, progress towards elimination or post-elimination surveillance). While forecasts may have such use in guiding timely IRS team mobilization in hyperendemic zones where earlier than usual malaria transmission is predicted, here the emphasis has been on epidemic regions. With this approach one can envisage forecast information aiding a wide range of district-level management decisions in countries still in the phase of malaria control (e.g. ensuring adequate drug supply to clinics and reassigning vector-control intervention actions to at-risk districts). District offices could also use forecasts to enhance information campaigns to vulnerable populations to increase bite-avoidance behaviour such as ensuring use of nets supplied in previous mass distribution campaigns. This may involve the combination of the malaria hazard forecasts with high spatial resolution modelling of population vulnerability which can change dramatically over small spatial scales.

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As a part of the QWeCI activity, in April 2013 the International Centre for Theoretical Physics (ICTP) in Trieste, Italy, hosted a school related to climate and health. Lectures given by a large number of experts and leaders in the field from across the globe were combined with many hands-on exercises for the participants to practice the techniques they had learned. The school was funded by ICTP, with additional generous support from the World Meteorological Organization.

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Further reading

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