September 2017

Fondazione Eni Enrico Mattei

Working Paper

044.2017

Burden of Climate Change on Malaria Mortality

Shouro Dasgupta

Climate Change: Economic Impacts and Adaptation Series Editor: Francesco Bosello

Burden of Climate Change on Malaria Mortality

By Shouro Dasgupta, Università Ca' Foscari, FEEM and CMCC

Summary

In 2015, an estimated 429,000 deaths and 212 million cases of malaria occurred worldwide, while 70% of the deaths occurred in children under five years old. Changes in climatic exposure such as temperature and precipitation make malaria one of the most climate sensitive outcomes. Using a global malaria mortality dataset for 105 countries between 1980 and 2010, we estimate that the global optimal temperature maximizing all-age malaria mortality is 20.6, lower than previously predicted in the literature. While in the case of child mortality, a significantly lower optimum temperature of 19.3° is estimated. Our results also suggest that in Africa and Asia, the continents where malaria is most prevalent malaria mortality is maximized at 28.4 and 26.3, respectively. Furthermore, we estimate that child mortality (ages 0-4) is likely to increase by up to 20 percent in some areas due to climate change by the end of the 21st century.

Keywords: Climate change, Malaria, Vector borne disease, Temperature, Precipitation

JEL Classification: C10, C23, Q54, Q56

Address for correspondence:
Shouro Dasgupta
Fondazione Eni Enrico Mattei
Isola di San Giorgio Maggiore, 8
30124 Venezia
Italy
E-mail: shouro.dasgupta@feem.it

Burden of Climate Change on Malaria Mortality

Shouro Dasgupta

Universita Ca' Foscari Venezia, Fondazione Eni Enrico Mattei, Centro Euro-Mediterraneo sui Cambiamenti Climatici

Email: shouro.dasgupta@feem.it

August 2017

Abstract

In 2015, an estimated 429,000 deaths and 212 million cases of malaria occurred worldwide, while 70% of the deaths occurred in children under five years old Changes in climatic exposure such as temperature and precipitation makes malaria one of the most climate sensitive outcomes. Using a global malaria mortality dataset for 105 countries between 1980 and 2010, we estimate that the global optimal temperature maximizing all-age malaria mortality is 20.6℃, lower than previously predicted in the literature. While in the case of child mortality, a significantly lower optimum temperature of 19.3° is estimated. Our results also suggest that in Africa and Asia, the continents where malaria is most prevalent malaria, mortality is maximized at 28.4℃ and 26.3℃, respectively. Furthermore, we estimate that child mortality (ages 0-4) is likely to increase by up to 20 percent in some areas due to climate change by the end of the 21^{st} century.

Keywords: Climate change, Malaria, Vector borne disease, Temperature, Precipitation

1 Introduction

In 2015, an estimated 429,000 deaths and 212 million cases of malaria occurred worldwide, while 70% of the deaths occurred in children under five years old (WHO, 2016). The balance between temperature and precipitation is critical for breeding and transmission of malaria vectors and hence for the transmission of malaria. Although, the fact climatic variables affect malaria transmission is known (Alonso et al., 2011), the impact of climatic exposure on malaria mortality is less clear.

Malaria is one of the most widely transmitted vector-borne diseases, according to the World Health Organization (WHO); the death burden of malaria has increased over the last decade (WHO, 2010). Vector-borne diseases (VBD) are infections transmitted by the bite of infected arthropod species such as mosquitoes, ticks, triatomine bugs, sandflies, and blackflies. These are among the major microbial causes of morbidity and mortality in the world today affecting nearly half of the world's population, the majority of who reside in developing countries located in the tropical and subtropical climate (WHO, 2016).

Malaria is considered one of the most sensitive to changing environmental conditions (Martens, 1998; Martens et al., 1999; Rogers and Randolph, 2000; and Kim et al., 2012); it is also the most deadly and widespread. In 2014, ninety-seven countries and territories had malaria transmission while an estimated 1.2 billion people were at high risk [1]. We utilize an annual global dataset over a span of 30 years to investigate the relationship between climatic exposure (temperature and various measures of extreme precipitation) and malaria mortality. The climatic data for this paper comes from the Global Land Data Assimilation System (GLDAS), while the data on malaria deaths comes from the Institute for Health Metrics and Evaluation (IHME). Combining these datasets, we compute optimal climatic conditions for malaria mortality and provide projections due to climate change. Using population-weighted climate data for the malaria season in each country, we estimate that the optimal temperature to maximize mortality is significantly lower (20℃ 20°C and 23℃) than previously estimated. Furthermore, our results suggest that malaria mortality among children will increase by 11.5% by the end of 21st century due to climate change.

2 Determinants of Malaria Transmission

Changes in temperature influence the incubation period of malaria parasites and in turn malaria transmission rates. Temperature also affects the lifespan, growth, and biting rates of mosquitos (Lindsay et al., 1998; Craig et al., 1999; Grover-Kopec et al., 2005; and Gething et al., 2011); thus, the transmission rate of malaria is likely to have increased with rising temperature (Githeko, 2008). Rainfall often leads to stagnant water critical for breeding of mosquito eggs (Craig et al., 1999; Kiszewski et al., 2004; and Thomson et al., 2005). This makes malaria one of the most climate sensitive outcomes. While extreme rainfall events can synchronize vector host seeking and virus transmission, leading to increased malaria transmission and mortality (Patz et al., 2003 and Ermert et al., 2012). The optimal temperature for malaria transmission has often been considered between 20℃ and 30℃ (Casman and Dowlatabadi, 2002 and World Bank, 2012) but Martens et al. (1997) estimated it to be 31℃. While Mordecai et al., (2013), using thermal response functions conclude that the optimal temperature for malaria transmission is much lower at 25℃.

This paper computes the optimal conditions for temperature controlling for various indicators for extreme levels of precipitation to understand the impacts of these variables on the entire distribution of malaria mortality across countries over 30 years.

[1]Population at risk (High + Low): High=population living in areas (reported malaria incidence $>$ 1 per 1000/year) defined at administrative level 2 or lower. Low=population living in areas (reported malaria incidence $<$ 1 per 1000/year)

3 Literature Review

The relationship linking climatic variables and transmission of vector-borne diseases has been studied in both the medical science and the health economics literature. Many papers including Anderson and May (1992), Lindsay and Parson (1998,) and Lafferty (2009), used standard epidemiological models to study the relationship between the vectors and pathogens of malaria and temperature to conclude that reproductive rate of malaria vectors increases between 0.5 – 4.0% as temperature increases. A number of papers use biological models to estimate the effect of changing climatic variables on malaria also found similar results. Martens et al. (1999), controlling for vector specific information on malaria and dengue pathogens suggest that extreme temperature and periods of heat stress aid the reproduction and transmission rate of malaria. Chaves and Koenraadt (2010) use a similar model with data from four East African countries and found that an increase in number of heat days during a season increases malaria outbreaks.

Mouchet et al. (1996) conclude that a decrease in rainfall in the Sahel Region of Africa results in a decline in the transmission rate of malaria vectors. Thomson et al. (2005) controls for precipitation and sea-surface temperature in Botswana and find that the variability of the climatic variables can be used to explain nearly seventy per cent of the variability in the reported malaria incidences. While Singh and Sharma (2002) suggest that decrease in rainfall in central-India has negatively affected the productivity rate of larva responsible for malaria vectors and pathogens.

The existing literature on the relationship between climate change and transmission of vector-borne diseases mostly focuses either on individual countries (Githeko et al., 2000) or on specific sites within countries (Zhou et al., 2003). Moreover, quantifying the impacts of the climate variables has mostly involved incorporating changes in temperature in the models (Hoshen and Morse, 2004) despite the medical literature increasingly suggesting that both temperature and precipitation affect the transmission of malaria (Zhou et al., 2004 and Zhou et al., 2007).

Very few papers (e.g. Paaijmans et al., 2010 and Caminade et al., 2014) have studied the impact of climate exposure on malaria mortality; even these two papers use simulated models. A critical contribution of this paper is the estimation of global and continental optimal thresholds for temperature that maximizes malaria mortality.

4 Data and Descriptive Statistics

The climatic data has been extracted from Global Land Data Assimilation System (GLDAS) version 2, a land surface mode providing data at 1° by 1° and 3-hourly resolution (Rodell et al., 2004). GLDAS provides reanalysis gridded climatic data obtained by ingesting satellite and ground-based observational data products using advanced land surface modelling and data assimilation techniques to generate optimal fields of land surface states and fluxes (Rodell et al., 2004). Four land surface models and integrates a huge quantity of observation based data and executes globally at high resolutions (2.5° to 1 km) enabled by the Land Information System (LIS) (Kumar et al., 2006). To obtain the annual data, we averaged the extracted data by grid cell, aggregated the 3-hourly data into daily data, and then computed the annual measures.

4.1 Population Weighted Climatic Exposure

The high temporal-resolution of the climatic data allows us to control for the different lengths of transmission seasons across countries. This is particularly important for comparing countries with shorter transmission seasons (e.g. Burkina Faso and Mali) rather than year-round transmission (Congo and Cameroon). The temperature in the off-season, with very low or no transmission, has very little relevance for malaria and has been excluded from the analysis.

Furthermore, we aggregate the grid cell estimates of temperature and precipitation to the country-year level using gridded population weights using population weights for the year 2000 from the Gridded Population of the World (GPW, v3). Population weighted climatic data are critical as they more closely estimate the weather being experienced by the majority of the population and not the area. Population weighted aggregation also reduces biases in sparsely populated areas and areas with complex terrains, ensuring that the climatic data is more closely matched to locations where malaria morality occurs.

While we use mean temperature for malaria season, in the case of precipitation, we compute the Standardized Precipitation Index (SPI) at 3 and 6 months' scales from the gridded GLDAS data. The SPI is based on the probability of precipitation for any time scale. The major strength of SPI is that precipitation is the only input parameter required and that it can be computed for different time scales (McKee et al. 1993). The SPI calculation is based on the long-term precipitation (at least 20 − 30 years). The long-term record is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (Edwards and McKee 1997). Positive SPI values indicate greater than median precipitation and negative values indicate less than median precipitation [2].

We also use the 90^{th} and 99^{th} percentiles of the distribution of precipitation for each country; starting with the gridded data, we first compute the 90th/99th percentile of the distribution of precipitation for each grid for each year. Then we choose the corresponding maximum value of the gridded data for each country.

4.2 Malaria Mortality Data

The malaria mortality data comes from IHME's publication in The Lancet global estimates for malaria mortality - *Global malaria mortality between 1980 and 2010: a systematic analysis*. These estimates are based on data from 1,150 sites in 105 countries. Data from vital registration systems and from verbal autopsy studies were used for these estimates. The study uses a number of predictive models to estimate the malaria mortality with uncertainty by age, sex, country, and year − and includes critical predictors of malaria mortality such as Plasmodium falciparum, antimalarial drug resistance, and vector control and finally, out-of-sample predictive validity to select the final model.

4.3 Descriptive Statistics

Table 1 below provides the descriptive statistics. The average population weighted annual temperature in the overall panel is 22°C while the population weighted average precipitation is slightly over 1,100 mm per year.

Variable	Mean	Std. Dev.	Min	Max
Malaria Mortality	13,139	43,247	0	525,116
Mean Temperature	22	6.9	-0.8	33
Mean Precipitation	1,111.80	747.1	6.8	4,328
SPI (3 months)	0.01	0.4	-1.8	1.5
SPI (6 months)	-0.01	0.5	-2.6	2.1
Health Expenditure/GDP (%)	5.5	2.04	0.81	16.79

Table 1: **Descriptive Statistics**

[2] See Standardized Precipitation Index User Guide (`http://www.wamis.org/agm/pubs/SPI/WMO_1090_EN.pdf`) for more information on SPI.

The following figures show the classification (Figure 1, left-panel) and percentage of population at risk of malaria by country (Figure 1, right-panel). The population-risk map shows that the high majority of malaria cases occur in Africa (90% according to some estimates).

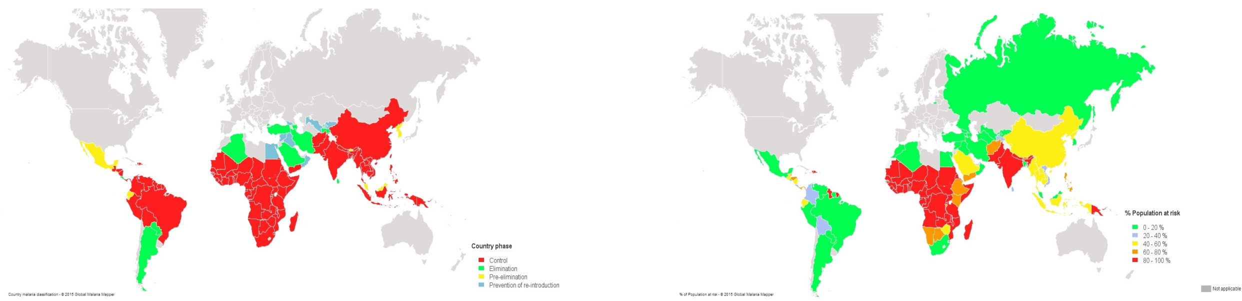

Figure 1: **Malaria classification (left-panel) and percentage of population at malaria risk by country in 2014 (right-panel).**

IPCC (2014) and WHO (2016) states that vector control is the single most efficient method of controlling transmission of malaria and that changes in climatic patterns may have decreased the rate of decline in mortality caused by malaria and at the same time may have increased the transmission rates in the years to come. This paper investigates this particular linkage with respect to temperature and various measures of precipitation.

5 Methodology

In order to estimate the impact of changes in the climatic variables of temperature and precipitation on malaria mortality, we use the following fixed-effects specification:

$$\gamma_{it} = \alpha_i + \phi_t + \beta_1 T_{it} + \beta_2 T_{it}^2 + P_{it}\beta_3 + \epsilon_{it} \tag{1}$$

where the subscripts i and t represent country and year fixed-effects, respectively;

- γ_{it} is the natural log of population malaria mortality rate in country i in year t.
- T_{it} is the population weighted average temperature during the malaria season while T_{it}^2 is the second-degree polynomial of temperature; the relationship between the climatic variables and malaria mortality is either concave or convex.
- P_{it} represents a vector of population weighted precipitation indices including SPI (3 and 6 months) and $90^{\text{th}}/99^{\text{th}}$ of the distribution of precipitation during the malaria season.
- All time-invariant factors influencing countries' malaria mortality such as health expenditure are accounted for by α_i (country specific fixed-effects), while the time variant factors such as malaria eradication and vaccination efforts are accounted for by ϕ_t (year specific fixed-effects)
- ϵ_{it} is a random error term.

6 Results and Discussion

The first set of regressions investigates the impact of climatic exposure on all-age malaria mortality using fixed-effects regressions with robust standard errors. As temperature increases, malaria mortality at first declines but increases beyond the threshold or the optimum level of temperature. The marginal plots shows a U-shaped relationship between temperature and malaria mortality in line with the literature. We find that country-level malaria mortality is a smooth, non-linear, and convex in temperature (Figure 2). Equation 1 predicts that malaria mortality is maximized at an optimum temperature of 20.6°C, much lower than the estimates by Mordecai et al. (2013) and Ryan et al. (2015).

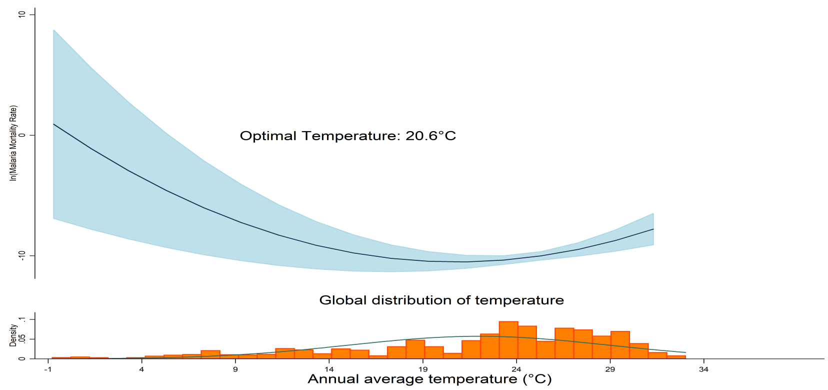

Figure 2: **Impact of temperature on all-age malaria mortality:** Global non-linear relationship between average seasonal temperature and log of malaria mortality (dark navy line, relative to the optimum) during 1980–2010 with 95% confidence interval (blue, with robust standard errors). Specification includes country and year fixed effects, and 99$^{\text{th}}$ percentile of precipitation. Histogram shows global distribution of temperature.

These results suggest although the malaria transmission rate declines with initial increases in temperature, as the mean temperature crosses a certain threshold, further increases in temperature starts to positively affect malaria mortality. This is a cause of concern, as the temperature continues to warm, malaria mortality may occur in countries that are currently below but close to this threshold. In the case of the precipitation controls, we find that an increase in 99$^{\text{th}}$ of precipitation results in a 1.1% increase in malaria mortality (Appendix I: Table A1), while the SPI indices (3 and 6 months), increases malaria mortality by 11% and 13.4%, respectively.

We also compute optimal conditions for Africa and Asia, the continents where malaria is most prevalent. In the case of all-age mortality, Equation (1) predicts that malaria mortality is maximized at 28.4°C and 26.3°C in Africa and Asia, respectively (Figure 3). These non-linear results will help in understanding the effects of climate change on malaria mortality.

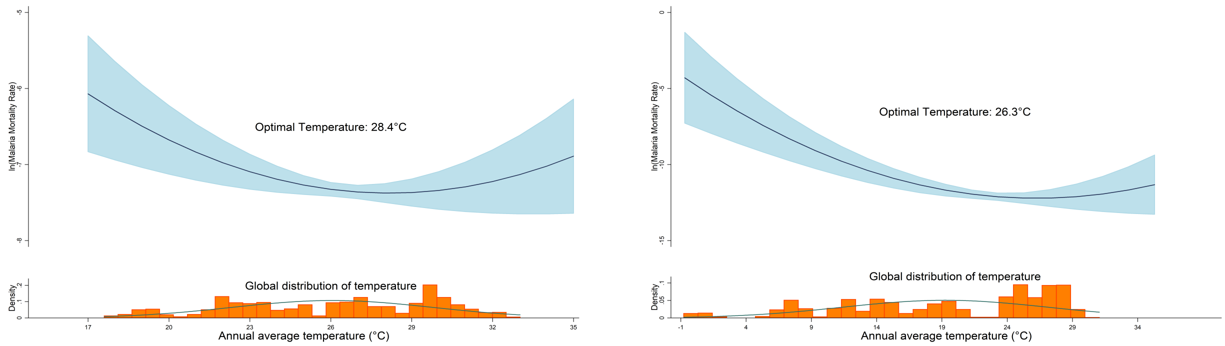

Figure 3: **Impact of temperature on all-age malaria mortality in Africa (left-panel) and Asia (right-panel):** Non-linear relationship between average seasonal temperature and log of malaria mortality (dark navy line, relative to the optimum) during 1980–2010 with 95% confidence interval (blue, with robust standard errors). Specification includes country and year fixed effects, and 99th percentile of precipitation. Histogram shows distribution of temperature.

The above results suggest that malaria mortality decreases with initial increases in temperature until the threshold is reached, beyond which malaria mortality increases. Results also show that increases in wetness levels as measured by 99th percentile of precipitation and SPI (3 and 6 months) increases malaria mortality significantly.

6.1 Infant Mortality

According to the IHME malaria mortality dataset, infants (ages 0 to 4) are at the highest risk of malaria mortality. We find that the global optimal temperature maximizing malaria mortality among children is 19.3℃ (1.3℃ lower than the optimum for all-age mortality). While, the optimal temperature to maximize malaria mortality in Africa is 28.2℃ (0.2℃ lower than that for all-age mortality). The marginal plots (Figure 4) show that the U-shaped relationship between temperature and malaria mortality continues to hold for mortality in this age bracket as well.

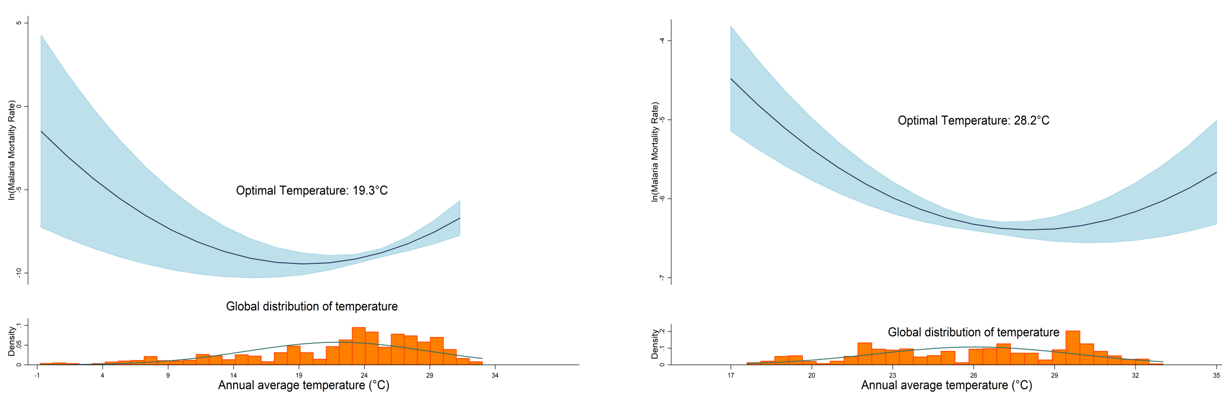

Figure 4: **Impact of temperature on child malaria mortality (0 – 4); Global (left-panel) and Africa (right-panel):** Non-linear relationship between average seasonal temperature and log of malaria mortality among children (dark navy line, relative to the optimum) during 1980–2010 with 95% confidence interval (blue, with robust standard errors). Specification includes country and year fixed effects, and 99th percentile of precipitation. Histogram shows distribution of temperature.

As for precipitation controls, increases in the 99th percentile of precipitation increases malarial mortality in children by 1%, while increases in one unit in 3-months and 6-months SPI increase malarial mortality by 9.7% and 12.8%, respectively (Annex I: Table A3). These increases are slightly lower than the estimates for all-age malaria mortality.

6.2 Spatial Analysis

It is likely that malaria transmission, hence malaria mortality, across countries is spatially correlated, thus it is important to utilize spatial regression to incorporate this spatial dependence. We use a negative exponential based spatial weight, where the spatial dependence between countries decreases as the distance between the geographic centers of the countries increases. Building on Equation 1, we incorporate the spatial weight to account for the spatial structure of the data, which can be expressed as Equation 2 below:

$$\gamma_{it} = \rho_W \gamma_{ij} + X\beta_{ij} + \epsilon_{ij} \tag{2}$$

where ρ is a spatial autoregressive coefficient, ϵ_{ij} is a vector of error terms, and W is the spatial weight matrix, the rest of the variables remain the same from Equation 1.

In the case of all-age mortality, Equation 2 predicts that malaria mortality is maximized at between 21.5℃ and 22℃ (Appendix I: Table A4, columns 1-3), higher than that estimated (20.6℃) using the fixed-effects regressions. In the case of child malaria mortality (age bracket of 0 to 4), we find that the optimal temperature for malaria mortality is between 21.1℃ and 21.8℃[3] (Appendix I: Table A4, columns 4-6), higher than the optimal temperature predicted by Equation 1. However, these optimal conditions are still significantly lower than predicted previously. The impact of precipitation controls are very similar to the estimates from the fixed-effects regressions.

6.3 Burden of Climate Change

We estimate the impact of warming on global and national level malaria mortality (all-age and child) by combining our non-linear estimations with Representative Concentration Pathway (RCP) 8.5 of future warming by the end of the century. Our temperature changes are the population-weighted country level projections averaged across all CMIP5 models. This particular approach assumes that the response of malaria mortality to future warming is similar to that of today. The estimates of country-specific warming are the ensemble mean projected warming for RCP8.5 across all global climate models contributing to CMIP5 [4].

By the end of the 21st century, we estimate that unmitigated climate change will increase all-age malaria mortality by 2.6%. All-age malaria mortality is projected to increase in all the countries where malaria is currently present (Figure 5, left-panel), with Sri Lanka and Philippines experiencing the highest increases. In the case of malaria mortality for the ages 0 to 4, our estimates suggest that malaria mortality in this age-bracket is projected to increase by 11.6% on average (median of 11.4%) due to climate change by the of the century (Figure 5, right-panel), with some countries experiencing 20% increases. The projected increase for child mortality (70% of total malaria mortality) is significantly higher due to the lower optimal temperature.

[3] Depending on the precipitation control

[4] Multi-model mean RCP 8.5 experiments of ACCESS1-0, ACCESS1-3, bcc-csm1-1, BNU-ESM, CanESM2, CCSM4, CESM1-BGC, CESM1-CAM5, CMCC-CM, CMCC-CMS, CNRM-CM5, CSIRO-Mk3-6-0, EC-EARTH, FGOALS-g2, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, and GISS-E2.

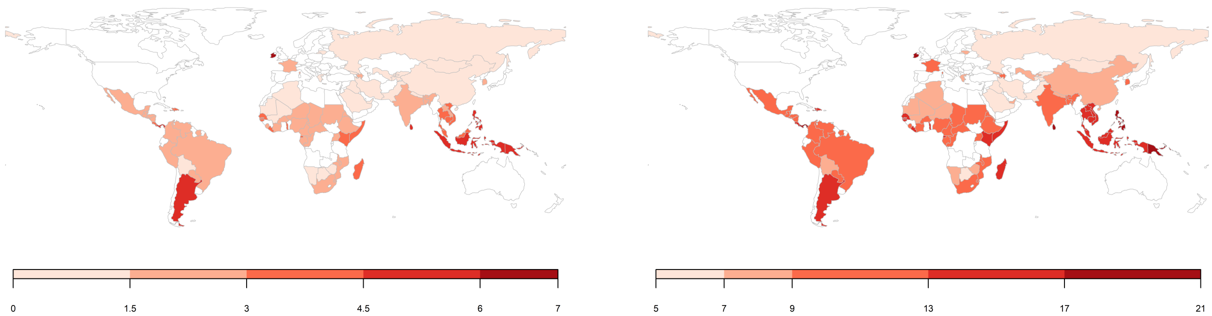

Figure 5: **Projected impact of climate change on malaria mortality; all-age (left-panel) and ages 0 to 4 (right-panel):** Change in malaria mortality due to temperature change (RCP 8.5) by the end of 21^{st}. The median change in all-age malaria is projected to be 2.5% (maximum increase of 6.2%); while the median increase in child malaria mortality is projected to be 11.4%, with a maximum of 20.3%. Projections are computed using a population-weighted average of country-level temperature change under RCP 8.5.%.

7 Conclusion

This paper examines the relationship between population weighted climatic exposure and malaria mortality in a cross-country paradigm using panel data between 1980 and 2010. We find that the relationship between temperature and malaria mortality is highly non-linear. As temperature increases, malaria mortality initially declines but as temperature crosses a threshold, malaria mortality increases. Optimal temperature for countries that the global optimal temperature to maximize all-age and child malaria mortality is 20.6℃, lower than the estimates by Mordecai et al. (2013) and Ryan et al. (2015). This is a cause for concern, as it would require lower degrees of increases in temperature to increase the malaria mortality in these countries and most countries in Sub-Saharan Africa have annual mean temperatures between 20 and 28℃ - containing the optimum conditions to maximize malaria related mortality. In the case of child mortality, we find a significantly lower optimum temperature of 19.3°, this is highly critical as the majority of malaria related mortality occurs among children. The continental specifications predict that malaria mortality is maximized at 28.4 and 26.3℃ in Africa and Asia, respectively – the continents where malaria is most prevalent.

As for precipitation controls, we estimate that increases in one unit of 3 and 6 months SPI results in approximately 10% increases in malaria mortality – suggesting that controlling for extreme precipitation conditions is critical. Furthermore, combining our non-linear estimates with RCP 8.5, we estimate that due to climate change, all-age malaria mortality will increase by up to 7% in some countries, while child mortality will increase significantly by up to 20%.

Our U-shaped marginal plots suggest that increasing temperature up to a certain decreases malaria mortality but beyond the threshold, any increases in mean temperature results in an increase in malaria mortality. This finding is consistent with the biological models used to study the impact of climatic variables on malaria transmission. Our results also are robust in that we use population-weighted climatic exposure during the malaria seasons across countries to ensure that we are controlling for the exposure as experienced by the population in a country. We also use spatial regressions to control for any spatial dependence of malaria transmission to validate our results. The non-linear results will help in understanding the effects of climate change on malaria mortality.

References

Alonso P.L., Brown G., Arevalo-Herrera M., Binka F., Chitnis C., Collins F. (2011). A Research Agenda to Underpin Malaria Eradication. PLoS Med 8(1): e1000406. doi:10.1371/journal.pmed.1000406

Anderson, R. M., and May, R. M. (1992). Infectious Diseases of Humans, Dynamics and Control. Oxford, UK: Oxford University Press.

Caminade, C., Kovats, S., Rocklov, J., Tompkins, A. M., Morse, A. P., Colón-González, F. J., Stenlund, H., Martens, P., and Lloyd, S. J. (2014). Impact of climate change on global malaria distribution, Proc. Natl. Acad. Sci. USA, 111, 3286–3291.

Casman E.A. and Dowlatabadi H. (2002). The Contextual Determinants of Malaria. Resources for the Future Press; Washington, DC. pp. 93–109.

Center for International Earth Science Information Network-CIESIN-Columbia University, UN-FAO, and Centro Internacional De Agricultura Tropical-CIAT. (2005). Gridded Population of the World, Version 3 (GPWv3): Population Count Grid [Data set]. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/h4639mpp.

Chaves, L.F. and C.J. Koenraadt. (2010). Climate change and highland malaria: Fresh air for a hot debate. Q Rev. Biology 85(1), 27-55.

Craig M.H., Snow R.W., and le Sueur D. (1999). A climate-based distribution model of malaria transmission in sub-Saharan Africa. Parasitology Today, 15: 105-111.

Edwards, D. C. and T. B. McKee (1997). Characteristics of 20th century drought in the United States at multiple time scales. Climatology Report No. 97-2, Colorado State Univ., Ft. Collins, CO.

Ermert V., Fink A. H., Morse A. P., and Paeth H. (2012). The impact of regional climate change on malaria risk due to greenhouse forcing and land-use changes in tropical Africa. Environ. Health Perspective. 120, 77–84 10.1289/ehp.1103681.

Gething P.W., Van Boeckel T., Smith D.L., Guerra C.A., Patil A.P., Snow R.W., and Hay S.I. (2011). Modeling the global constraints of temperature on transmission of Plasmodium falciparum and P. vivax. Parasit Vectors, 4:92.

Githeko, A. (2008). A. Malaria, Climate Change and Possible Impacts on Populations in Africa. In International Studies in Population. HIV Resurgent Infections and Population Change in Africa. (M. Carael, and J. R. Glynn, Eds.) New York, NY: Springer.

Githeko, A. K., Lindsay, S. W., and Confalonieri, U. E. (2000). Climate change and Vector- Borne Diseases: a Regional Analysis. Bulletin of the World Health Organization: 78 (9), pp. 1136-1147.

Grover-Kopec E.K., Kawano M., Klaver R.W., Blumenthal M.B., Ceccato P., Connor S.J. (2005). An online operational rainfall-monitoring resource for epidemic malaria early warning systems in Africa. Malaria Journal, 4:6.

IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Kim Y.M., Park J.W., and Cheong H.K. (2012). Estimated effect of climatic variables on the transmission of plasmodium vivax malaria in the Republic of Korea. Environ Health Perspective. 120 (9): 1315.

Kiszewski A., Mellinger A., Spielman A., Malaney P., Sachs S.E., and Sachs J. (2004). A global index representing the stability of malaria transmission. American Journal of Tropical Medicine and Hygiene; 70:486–498.

Kumar, S. V., C. D. Peters-Lidard, Y. Tian, P. R. Houser, J. Geiger, S. Olden, L. Lighty, J. L. Eastman, B. Doty, P. Dirmeyer, J. Adams, K. Mitchell, E. F. Wood, and J. Sheffield. (2006). "Land Information System - An interoperable framework for high resolution land surface modelling", Environ. Modelling and Software, 21, 1402-1415.

Lafferty K.D. (2009). The ecology of climate change and infectious diseases. Ecology 90:888–900.

Lindsay, S., Bodker, R., and Malima, R. (1999). 0. Effect of 1997-98 El Ni?o on highland malaria in Tanzania. The Lancet: 355, 989-990.

Martens, W. J. M., Jetten, T. H. and Focks, D. A. (1997). Sensitivity of malaria, schistosomiasis and dengue to global warming. Clim. Change 35, 145–156.

Martens P., Niessen L.W., Rotmans J., Jetten T.H., and McMichael A.J. (1998). Potential impact of global climate change on malaria risk. Environmental Health Perspective. 103: 458–64.

Martens P., Kovats S., Nijhof S., et al. (1999). Climate change and future populations at risk of malaria. Global Environmental Change. 9 (Special issue): 89—107.

McKee, T. B., N. J. Doesken, and J. Kleist. (1993). The relationship of drought frequency and duration of time scales. Eighth Conference on Applied Climatology, American Meteorological Society, Anaheim CA, pp.179-186.

Mordecai, Erin A., Krijn P. Paaijmans, and Leah R. Johnson. (2013). Optimal Temperature for Malaria Transmission Is Dramatically Lower than Previously Predicted. Ecologic Letters; 16(1): 22–30.

Mouchet, J. S., Manuin, S., Sircoulon, S., Laventure, S., Faye, A. W., Onapa, P., et al. (1998). Evolution of malaria for the past 40 years: impact of climate and human factors. Journal of the American Mosquito Control Association: 14, 121–130.

Murray C.J.L, Rosenfeld L.C., Lim S.S., Andrews K.G., Foreman K.J., Haring D., Fullman N., Naghavi M., Lozano R., Lopez A.D. (2012). Global malaria mortality between 1980 and 2010: a systematic analysis. The Lancet; 379:413-431.

Paaijmans, K. P., Simon Blanford, and Andrew S. Bell. (2010). Influence of Climate on Malaria Transmission Depends on Daily Temperature Variation. Proceedings of National Academy Sciences; 107: 15135–15139.

Patz, J.A. (2003). A.K. Githeko, J.P. McCarty, S. Hussain, U. Confalonieri, N. de Wet Climate change and infectious diseases: Word Health Organization (2003)

Rodell, M. and P. R. Houser (2004). "Updating a land surface model with MODIS derived snow cover", Journal of Hydromet., 5(6), 1064-1075.

Rogers, D.J. and Randolph S.E. (2000). The global spread of malaria in a future, warmer world. Science 2000; 289: 1763–66.

Ryan S.J., McNally A., Johnson K.R., Mordecai E.A., Ben-Horin T., Paaijmans K., Lafferty K.D. (2015). Mapping Physiological Suitability Limits for Malaria in Africa under Climate Change. Vector-Borne Zoonotic Dis; 15(12):718–725. doi: 10.1089/vbz.2015.1822

Singh, N. and Sharma, V. P. (2002). Patterns of rainfall and malaria in Madhya Pradesh (central India). Ann. Trop. Med. Parasite: 965, 349-359.

Thomson, M. C., Mason, S. J., Phindela, T., and Connor, S. J. (2005). Use of Rainfall and sea surface temperature monitoring for malaria early warning in Botswana. American Journal of Tropical Medicine and Hygiene: 73, 214-221.

WHO. (2010) Health systems financing: the path to universal coverage. Geneva: WHO. Available: http://www.who.int/malaria/publications/world-malaria-report-2016/report/en/.

WHO. (2016). World Malaria Report 2016. Geneva: WHO. Available: http://www.who.int/whr/2010/en/index.html. Accessed 21 September 2010.

Zhou, G., Noboru, M., and Yan, G. (2003). Association between climate variability and malaria epidemic in the east African highlands. Proc. Natl. Acad. Sci USA: 101, 2375-2380.

Zhou G., Minakawa N., Githeko A. K., Yan G. (2005). Climate variability and malaria epidemics in the highlands of East Africa. Trends in Parasitology 21(2):54 –56.

Zhou G., Munga S., Minakawa N., Githeko A. K., and Yan G. (2007). Spatial relationship between adult malaria vector abundance and environmental factors in western Kenya highlands. American Journal of Tropical Medicine and Hygiene 77(1):29 –35.

Annex I

Table A1: Global Regressions (All-age and child mortality)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Log of Malaria Mortality (All age)			Log of Malaria Mortality (Ages 0 - 4)		
Mean Temperature	-1.013***	-1.017***	-1.016***	-0.750***	-0.749***	-0.747***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Mean Temperature Squared	0.025***	0.025***	0.025***	0.019***	0.019***	0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
99^{th} percentile of Precipitation	0.011***			0.010***		
	(0.000)			(0.000)		
SPI (3-months)		0.110*			0.097*	
		(0.054)			(0.064)	
SPI (6-months)			0.134***			0.128***
			(0.004)			(0.003)
Observations	2,143	2,143	2,143	2,112	2,112	2,112
R-squared	0.247	0.233	0.237	0.356	0.343	0.347
Number of Countries	83	83	83	83	83	83
Adj. R-squared	0.236	0.221	0.225	0.345	0.332	0.337

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.10, + p<0.15

Table A2: Continental Regressions – Africa and Asia (All-age malaria mortality)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		Africa			Asia	
Mean Temperature	-0.530***	-0.504***	-0.534***	-0.572***	-0.562***	-0.560***
	(0.002)	(0.005)	(0.003)	(0.000)	(0.000)	(0.000)
Mean Temperature Squared	0.009***	0.009***	0.009***	0.011***	0.010***	0.010***
	(0.005)	(0.008)	(0.005)	(0.001)	(0.003)	(0.004)
99^{th} percentile of Precipitation	0.002*			0.003*		
	(0.083)			(0.060)		
SPI (3-months)		0.049+			-0.042	
		(0.126)			(0.487)	
SPI (6-months)			0.022			-0.031
			(0.336)			(0.480)
Observations	1,064	1,064	1,064	644	644	644
R-squared	0.358	0.358	0.357	0.789	0.788	0.788
Number of iso3	37	37	37	29	29	29
Adj. R-squared	0.314	0.313	0.312	0.767	0.766	0.766

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.10, + p<0.15

Table A3: Continental Regressions – Africa and Asia (Ages 0 - 4)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		Africa			Asia	
Mean Temperature	-0.850***	-0.816***	-0.836***	-0.137+	-0.132+	-0.128+
	(0.000)	(0.000)	(0.000)	(0.104)	(0.119)	(0.130)
Mean Temperature Squared	0.015***	0.015***	0.015***	0.004*	0.003+	0.003
	(0.000)	(0.000)	(0.000)	(0.062)	(0.138)	(0.157)
99th percentile of Precipitation	0.002			0.001		
	(0.165)			(0.349)		
SPI (3-months)		0.046*			-0.047	
		(0.099)			(0.215)	
SPI (6-months)			0.025			-0.038
			(0.198)			(0.160)
Observations	1,064	1,064	1,064	632	632	632
R-squared	0.279	0.279	0.279	0.923	0.924	0.924
Number of iso3	37	37	37	29	29	29
Adj. R-squared	0.229	0.229	0.228	0.915	0.915	0.915

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.10, + p<0.15

Table A4: Spatial Regressions (All-age and child mortality)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		Log of Malaria Mortality (All age)			Log of Malaria Mortality (Ages 0 - 4)	
Mean Temperature	-1.087**	-1.089**	-1.084**	-0.998**	-0.995**	-0.988**
	(0.036)	(0.039)	(0.039)	(0.023)	(0.025)	(0.025)
Mean Temperature Squared	0.025**	0.025**	0.025**	0.023**	0.023**	0.023**
	(0.022)	(0.023)	(0.021)	(0.012)	(0.012)	(0.011)
99th percentile of Precipitation	0.006**			0.006***		
	(0.040)			(0.009)		
SPI (3-months)		0.075+			0.091*	
		(0.123)			(0.056)	
SPI (6-months)			0.086**			0.106**
			(0.041)			(0.012)
Observations	1,490	1,490	1,490	1,476	1,476	1,476
R-squared	0.456	0.451	0.452	0.564	0.560	0.563
Number of Countries	58	58	58	58	58	58
Adj. R-squared	0.443	0.438	0.439	0.554	0.549	0.552

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.10, + p<0.15

Annex II – List of Countries

1	Afghanistan	43	Honduras	85	Sri Lanka
2	Angola	44	India	86	Sudan
3	Argentina	45	Indonesia	87	Suriname
4	Armenia	46	Iran	88	Swaziland
5	Azerbaijan	47	Iraq	89	Syria
6	Bangladesh	48	Kenya	90	Tajikistan
7	Belize	49	Korea, North	91	Tanzania
8	Benin	50	Korea, South	92	Thailand
9	Bhutan	51	Kyrgyzstan	93	Timor-Leste
10	Bolivia	52	Laos	94	Togo
11	Botswana	53	Liberia	95	Turkey
12	Brazil	54	Libya	96	Turkmenistan
13	Burkina Faso	55	Madagascar	97	Uganda
14	Burundi	56	Malawi	98	United Arab Emirates
15	Cambodia	57	Malaysia	99	Uzbekistan
16	Cameroon	58	Mali	100	Vanuatu
17	Central African Republic	59	Mauritania	101	Venezuela
18	Chad	60	Mauritius	102	Vietnam
19	China	61	Mexico	103	Yemen
20	Colombia	62	Morocco	104	Zambia
21	Comoros	63	Mozambique	105	Zimbabwe
22	Congo	64	Myanmar		
23	Congo, the Democratic Republic of the	65	Namibia		
24	Costa Rica	66	Nepal		
25	Côte d'Ivoire	67	Nicaragua		
26	Djibouti	68	Niger		
27	Dominican Republic	69	Nigeria		
28	Ecuador	70	Oman		
29	Egypt	71	Pakistan		
30	El Salvador	72	Panama		
31	Equatorial Guinea	73	Papua New Guinea		
32	Eritrea	74	Paraguay		
33	Ethiopia	75	Peru		
34	Gabon	76	Philippines		
35	Gambia	77	Rwanda		
36	Georgia	78	Sao Tome and Principe		
37	Ghana	79	Saudi Arabia		
38	Guatemala	80	Senegal		
39	Guinea	81	Sierra Leone		
40	Guinea-Bissau	82	Solomon Islands		
41	Guyana	83	Somalia		
42	Haiti	84	South Africa		

NOTE DI LAVORO DELLA FONDAZIONE ENI ENRICO MATTEI
Fondazione Eni Enrico Mattei Working Paper Series

Our Working Papers are available on the Internet at the following addresses:
http://www.feem.it/getpage.aspx?id=73&sez=Publications&padre=20&tab=1

NOTE DI LAVORO PUBLISHED IN 2017

1.2017, SAS Series, Anna Alberini, Milan Ščasný, The Benefits of Avoiding Cancer (or Dying from Cancer): Evidence from a Four-country Study

2. 2017, ET Series, Cesare Dosi, Michele Moretto, Cost Uncertainty and Time Overruns in Public Procurement: a Scoring Auction for a Contract with Delay Penalties

3.2017, SAS Series, Gianni Guastella, Stefano Pareglio, Paolo Sckokai, A Spatial Econometric Analysis of Land Use Efficiency in Large and Small Municipalities

4.2017, ESP Series, Sara Brzuszkiewicz, The Social Contract in the MENA Region and the Energy Sector Reforms

5.2017, ET Series, Berno Buechel, Lydia Mechtenberg, The Swing Voter's Curse in Social Networks

6.2017, ET Series, Andrea Bastianin, Marzio Galeotti, Matteo Manera, Statistical and Economic Evaluation of Time Series Models for Forecasting Arrivals at Call Centers

7.2017, MITP Series, Robert C. Pietzcker, Falko Ueckerdt, Samuel Carrara, Harmen Sytze de Boer, Jacques Després, Shinichiro Fujimori, Nils Johnson, Alban Kitous, Yvonne Scholz, Patrick Sullivan, Gunnar Luderer, System Integration of Wind and Solar Power in Integrated Assessment

8.2017, MITP Series, Samuel Carrara, Thomas Longden, Freight Futures: The Potential Impact of Road Freight on Climate Policy

9.2017, ET Series, Claudio Morana, Giacomo Sbrana, Temperature Anomalies, Radiative Forcing and ENSO

10.2017, ESP Series, Valeria Di Cosmo, Laura Malaguzzi Valeri, Wind, Storage, Interconnection and the Cost of Electricity Generation

11.2017, EIA Series, Elisa Delpiazzo, Ramiro Parrado, Gabriele Standardi, Extending the Public Sector in the ICES Model with an Explicit Government Institution

12.2017, MITP Series, Bai-Chen Xie, Jie Gao, Shuang Zhang, ZhongXiang Zhang, What Factors Affect the Competiveness of Power Generation Sector in China? An Analysis Based on Game Cross-efficiency

13.2017, MITP Series, Stergios Athanasoglou, Valentina Bosetti, Laurent Drouet, A Simple Framework for Climate-Change Policy under Model Uncertainty

14.2017, MITP Series, Loïc Berger and Johannes Emmerling, Welfare as Simple(x) Equity Equivalents

15.2017, ET Series, Christoph M. Rheinberger, Felix Schläpfer, Michael Lobsiger , A Novel Approach to Estimating the Demand Value of Road Safety

16.2017, MITP Series, Giacomo Marangoni, Gauthier De Maere, Valentina Bosetti, Optimal Clean Energy R&D Investments Under Uncertainty

17.2017, SAS Series, Daniele Crotti, Elena Maggi, Urban Distribution Centres and Competition among Logistics Providers: a Hotelling Approach

18.2017, ESP Series, Quentin Perrier, The French Nuclear Bet

19.2017, EIA Series, Gabriele Standardi, Yiyong Cai, Sonia Yeh, Sensitivity of Modeling Results to Technological and Regional Details: The Case of Italy's Carbon Mitigation Policy

20.2017, EIA Series, Gregor Schwerhoff, Johanna Wehkamp, Export Tariffs Combined with Public Investments as a Forest Conservation Policy Instrument

21.2017, MITP Series, Wang Lu, Hao Yu, Wei Yi-Ming, How Do Regional Interactions in Space Affect China's Mitigation Targets and Economic Development?

22.2017, ET Series, Andrea Bastianin, Paolo Castelnovo, Massimo Florio, The Empirics of Regulatory Reforms Proxied by Categorical Variables: Recent Findings and Methodological Issues

23.2017, EIA Series, Martina Bozzola, Emanuele Massetti, Robert Mendelsohn, Fabian Capitanio, A Ricardian Analysis of the Impact of Climate Change on Italian Agriculture

24.2017, MITP Series, Tunç Durmaz, Aude Pommeret, Ian Ridley, Willingness to Pay for Solar Panels and Smart Grids

25.2017, SAS Series, Federica Cappelli, An Analysis of Water Security under Climate Change

26.2017, ET Series, Thomas Demuynck, P. Jean-Jacques Herings, Riccardo D. Saulle, Christian Seel, The Myopic Stable Set for Social Environments

27.2017, ET Series, Joosung Lee, Mechanisms with Referrals: VCG Mechanisms and Multilevel Mechanism

28.2017, ET Series, Sareh Vosooghi, Information Design In Coalition Formation Games

29.2017, ET Series, Marco A. Marini, Collusive Agreements in Vertically Differentiated Markets

30.2017, ET Series, Sonja Brangewitz, Behnud Mir Djawadi, Angelika Endres, Britta Hoyer, Network Formation and Disruption - An Experiment - Are Efficient Networks too Complex?

31.2017, ET Series, Francis Bloch, Anne van den Nouweland, Farsighted Stability with Heterogeneous Expectations

32.2017, ET Series, Lionel Richefort, Warm-Glow Giving in Networks with Multiple Public Goods

33.2017, SAS Series, Fabio Moliterni, Analysis of Public Subsidies to the Solar Energy Sector: Corruption and the Role of Institutions

34.2017, ET Series, P. Jean-Jacques Herings, Ana Mauleon, Vincent Vannetelbosch, Matching with Myopic and Farsighted Players

35.2017, ET Series, Jorge Marco, Renan Goetz, Tragedy of the Commons and Evolutionary Games in Social Networks: The Economics of Social Punishment

36.2017, ET Series, Xavier Pautrel, Environment, Health and Labor Market

37.2017, ESP Series, Valeria Di Cosmo, Sean Collins, and Paul Deane, The Effect of Increased Transmission and Storage in an Interconnected Europe: an Application to France and Ireland

38.2017, MITP Series, Massimo Tavoni, Valentina Bosetti, Soheil Shayegh, Laurent Drouet, Johannes Emmerling, Sabine Fuss, Timo Goeschl, Celine Guivarch, Thomas S. Lontzek, Vassiliki Manoussi, Juan Moreno-Cruz, Helene Muri, Martin Quaas, Wilfried Rickels, Challenges and Opportunities for Integrated Modeling of Climate Engineering

39.2017, ESP Series, Lucia de Strasser, Calling for Nexus Thinking in Africa's Energy Planning

40.2017, EIA Series, Alice Favero, Robert Mendelsohn and Brent Sohngen, Can the global forest sector survive 11°C warming?

41.2017, EIA Series, Malcolm N. Mistry, Ian Sue Wing, Enrica De Cian, Simulated vs. Empirical Weather Responsiveness of Crop Yields: U.S. Evidence and Implications for the Agricultural Impacts of Climate Change

42.2017, ET Series, Carlo Drago, Interval Based Composite Indicators

43.2017, EIA Series, Emanuele Massetti and Robert Mendelsohn, Do Temperature Thresholds Threaten American Farmland?

44.2017, EIA Series, Shouro Dasgupta, Burden of Climate Change on Malaria Mortality

Fondazione Eni Enrico Mattei
Corso Magenta 63, Milano – Italia

Tel. +39 02.520.36934
Fax. +39.02.520.36946

E-mail: letter@feem.it
www.feem.it