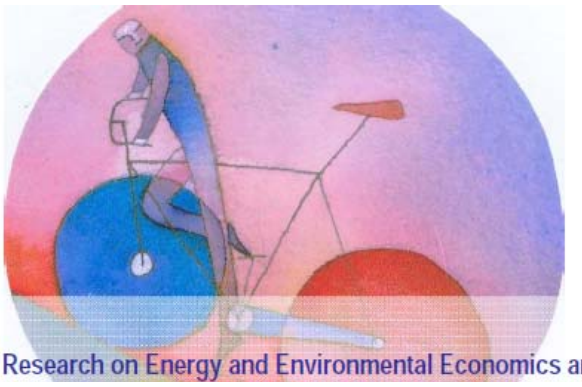

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# The Health Effects of Climate Change: A Survey of Recent Quantitative Research

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# The Health Effects of Climate Change:

# a Survey of Recent Quantitative Research

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**Abstract.** In recent years there has been a large scientific and public debate on climate change and its direct as well as indirect effects on human health. According to World Health Organization (WHO, 2006), some 2.5 million people die every year from non-infectious diseases directly attributable to environmental factors such as air pollution, stressful conditions in the workplace, exposure to chemicals such as lead, and exposure to environmental tobacco smoke. Changes in climatic conditions and climate variability can also affect human health both directly and indirectly, via changes in biological and ecological processes that influence the transmission of several infectious diseases (WHO, 2003). In the past fifteen years a large amount of research on the effects of climate changes on human health has addressed two fundamental questions (WHO, 2003). First, can historical data be of some help in revealing how short-run or long-run climate variations affect the occurrence of infectious diseases? Second, is it possible to build more accurate statistical models which are capable of predicting the future effects of different climate conditions on the transmissibility of particularly dangerous infectious diseases? The primary goal of this paper is to review the most relevant contributions which have directly tackled those questions, both with respect to the effects of climate changes on the diffusion of non-infectious and infectious diseases. Specific attention will be drawn on the methodological aspects of each study, which will be classified according to the type of statistical model considered. Additional aspects such as characteristics of the dependent and independent variables, number and type of countries investigated, data frequency, temporal period spanned by the analysis, and robustness of the empirical findings are examined.

**Keywords.** Climate change; Health; Statistical models; Non-infectious diseases; Infectious diseases; Malaria; Cardiovascular diseases.

**JEL classification.** C2; C3; I1; Q54.

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# 1. Introduction. Some facts and opinions on the relationship between climate change and health

In recent years there has been a large scientific and public debate on climate change and its direct as well as indirect effects on human health.

According to World Health Organization (WHO, 2006), some 2.5 million people die every year from non-infectious diseases directly attributable to environmental factors such as air pollution, extreme weather events, stressful conditions in the workplace, exposure to chemicals such as lead, and exposure to environmental tobacco smoke.

In particular, lead exposure has been estimated to account for 2% of the ischaemic heart disease burden and 3% of the cerebrovascular disease burden (WHO, 2003). Exposure to outdoor air pollution accounted for approximately 2% of the global cardiopulmonary disease burden (WHO, 2003). In the US, about 12% of the ischaemic heart disease burden has been related to occupation, for the age group 20-69 years. This estimate has been based on the specific risk factors of job control, noise, shift work and environmental tobacco smoke at work (Steenland et al., 2003). In Finland, it has been estimated that occupational risks account for 17% of the deaths from ischaemic heart disease, and 11% of those from stroke (Nurminen and Karjalainen, 2001). In Denmark, the occurrence of cardiovascular diseases is related to the type of occupation. Specifically, a reduction of 16% (22%) in the cardiovascular disease burden can be attributable to men (women) with non-sedentary occupations (Olsen and Kristensen, 1991).Changes in climatic conditions and climate variability represent a further factor which can affect human health directly or indirectly via changes in biological and ecological processes that influence the transmission of several infectious diseases (WHO, 2003). Direct effects on human health include, for example, thermal stresses due to increased frequency and intensity heat waves (cardiovascular and respiratory diseases, heat exhaustion), and deaths and injuries due to extreme weather events. Indirect effects include malnutrition, food-, water- and vector-borne diseases, together with increased morbidity due to the combined effect of exposure to high temperature and air pollution.

Empirical evidence suggests that malaria varies seasonally in highly endemic areas and is probably the vector-borne disease more sensitive to long-run climate changes. For example, the comparison of monthly climate and malaria data in highland Kakamega, Western Kenya, highlights a close

association between malaria transmission and monthly maximum temperature anomalies over the years 1997-2000 (Githeko and Ndegwa, 2001). The effects of soil moisture to determine the causal links between weather and malaria transmission has been studied by Patz et al. (1998). For the most common mosquito species *Anopheles gambiae*, the soil moisture predicts up to 45% and 56% of the variability of human biting rate and entomological inoculation rate, respectively. The link between malaria and extreme climatic events has long been the subject of study on the Indian subcontinent as well as in various other countries. Early in the twentieth century, the Punjab region experienced periodic epidemics of malaria. Excessive monsoon rainfall and the resultant high humidity were clearly identified as major factors in the occurrence of malaria epidemics. More recently, time-series analyses have shown that the risk of a malaria epidemic increased approximately five-fold during the year following an El Niño year in Indian region (Bouma and van der Kaay, 1994). Furthermore, a strong correlation is found between both annual rainfall and the number of rainy days and the incidence of malaria in most districts of Rajasthan and in some districts in Gujarat (Akhtar and McMichael, 1996). The relationship between reported malaria cases and El Niño has been documented for Venezuela, where, during the whole twentieth century, malaria rates increased on average by over one-third in the year immediately following an El Niño year (Bouma and Dye, 1997).

However, it is widely acknowledged that climate changes are only one of many important factors influencing the incidence of infectious diseases and that their effects are very unlikely to be independent of socio-demographic factors (e.g. human migrations, transportation, nutrition), or of environmental influences (e.g. deforestation, agricultural development, water projects, urbanization). In particular, it has been estimated that about 42% of the global malaria burden, or half a million deaths annually, could be prevented by environmental management, although this proportion varies significantly across different regions: it is 36% in the Eastern Mediterranean Region; 40% in the Western Pacific Region; 42% in sub-Saharan Africa; 42% in the South-East Asia Region; 50% in the European Region; 64% in the Region of the Americas (WHO, 2006).

Nevertheless, in the past fifteen years a large amount of research on the effects of climate changes on human health has addressed two fundamental questions (WHO, 2003). First, can historical data be of some help in revealing how short-run or long-run climate variations affect the occurrence of infectious diseases? Second, is it possible to build more accurate statistical models which are capable to predict the future effects of different climate conditions on the transmissibility of particularly dangerous infectious diseases?

The primary goal of this work is to review the most relevant contributions which have directly tackled those questions, with respect to the effects of climate changes on the diffusion of non-infectious and infectious diseases. Specific attention will be drawn on the methodological aspects of each study, which will be classified according to the specific problem in question, as well as the type of statistical model considered.[1]

As far as the specific problem addressed by each study is concerned, we refer to:

- **Primary studies**, which analyze the direct effects of rising temperatures on the burden of diseases;

- **Secondary studies**, which consider socio-economic effects of temperatures growth including Integrated Assessment Models (IAMs), General Equilibrium Models (GEMs) and Global Trade Analysis Project Models (GTAP);

- **Comparative Risk Assessments** (CRA), which integrate climate models for projecting future climate changes and "primary studies" for estimating the effects on health.

In terms of the type of statistical model which each of the surveyed study is based on, the following broad classes emerge:

- **Stationary and non-stationary time series models**, such as ARMAX (Auto Regressive Moving Average with exogenous variables) models, ECM (Error Correction Models), possibly with seasonal components;

- **Non-parametric forecasting models**, such as single and double exponential smoothing, Holt-Winters methods (additive, no seasonal, multiplicative);

- **Panel data and spatial models,** such as fixed and random effects models, dynamic panel data models, spatial lag and spatial error models.

The paper is organized as follows. Section 2 presents a taxonomy of the most popular classes of statistical models used to analyze the relationship between climate variations and the diffusion of non-infectious and infectious diseases. In Section 3 a significant number of quantitative contributions are discussed in detail, with particular emphasis on the specific problem addressed, as well as the type of statistical model adopted. Section 4 contains some conclusions.

[1] Additional aspects such as characteristics of the dependent and independent variables, number and type of countries investigated, data frequency, temporal period spanned by the analysis, and robustness of the empirical findings are examined.

# 2. Statistical models for the relationship between climate change and health: a taxonomy

Statistical models are important tools for analysing the complex relationship between climate changes and human health, since they allow researchers to link crucial climate variables (such as temperature and precipitations) at global or regional levels to the occurrence of the disease under scrutiny (WHO, 2003).

In this section, we briefly describe the basic specification for each class of models. We start with univariate models for stationary and non-stationary time series, such as ARMAX with exogenous variables, and ECM. The concepts of deterministic and stochastic trends are revisited, as well as the implications of cointegration and seasonality. We then present the most popular single-equation exponential smoothing methods for predicting the future values of a time-series. Finally, we consider the basic models for static and dynamic panel data, as well as for spatial statistics.

## 2.1. Models for stationary and non-stationary time series

In applied statistics, the standard model that takes into account the random nature and time correlations of the variable under study (e.g. the occurrence of a particular disease), $Y_t$, $t$=1,…,$T$, is the Auto Regressive Moving Average (ARMA) model (see, among others, Lütkepohl and Krätzig, 2004). It is composed of two parts: the autoregressive component and the moving average component. The autoregressive (AR) model of order $p$, AR($p$), can be written as:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + .... + \alpha_{t-p} Y_{t-p} + \varepsilon_t \qquad (1)$$

where $\alpha_0$ is a constant and $\varepsilon_t$, $t=p+1, \ldots, T$, are the error terms, generally assumed to be independent and identically-distributed normal random variables, with $E(\varepsilon_t)=0$ and $Var(\varepsilon_t)=\sigma^2$, for any $t$ (i.e. white noise errors). The parameters $\alpha_1, \alpha_2, ....., \alpha_p$ are referred to as the AR coefficients.

The moving average (MA) models can be interpreted as the representation of a time series which is generated by passing a white noise process through a non recursive linear filter. The notation MA($q$) refers to the moving average model of order $q$:

$$Y_t = \theta_0 + \varepsilon_t + \theta_1 \varepsilon_{t-1} + .... + \theta_q \varepsilon_{t-q} \tag{2}$$

A linear model for $Y_t$ based on both past values (1) and innovation values (2) is known as an Auto Regressive Moving Average (ARMA). The notation ARMA($p$,$q$) refers to $p$ autoregressive terms and $q$ moving average terms:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{3a}$$

or

$$\alpha(L) Y_t = \alpha_0 + \theta(L) \varepsilon_t \tag{3b}$$

where $\alpha(L)$ and $\theta(L)$ are polynomials in the lag operator $L$ of order $p$ and $q$, respectively.

In order to describe the relationship between the occurrence of a specific disease and climatic variables more accurately, an Auto Regressive Moving Average model with eXogenous variables (ARMAX) can be used. The notation ARMAX($p$,$q$,$b$) refers to a model with $p$ autoregressive terms, $q$ moving average terms and $b$ exogenous variables. This model nests the AR($p$) and MA($q$) models,

and linear combinations of $b$ explanatory variables, $X_{r,t-sr}$, $r$=1,…,$b$, $sr$=0,…,$wr$. An ARMA($p$,$q$,$b$) model can be written as:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{s1=0}^{w1} \delta_{1,s1} X_{1,t-s1} + \ldots + \sum_{sb=0}^{wb} \delta_{b,sb} X_{b,t-sb} + \varepsilon_t \quad (4)$$

A number of variations of ARMA models are commonly used in statistics, according to whether the series $Y_t$ and $X_{r,t}$ are integrated or exhibit seasonalities. We explain the concept of integration below.

It is well known that classical statistical inference is based on the concept of stationarity. A time series $Y_t$, $t$=1,...,T, is said to be (weakly) stationary if E($Y_t$) and Var($Y_t$) are constant for any $t$ and finite, and Cov($Y_t$, $Y_{t-k}$)=Cov($Y_s$, $Y_{s-k}$), for $t$ different from $s$ (what matters is only $k$, not the time location). At the same time, it is widely acknowledged that most economic, social-demographic, environmental and climatic time series are non-stationary, since they contain trends (deterministic and/or stochastic).

The simplest example of a non-stationary time series with a stochastic trend is the Random Walk (RW), i.e. the AR($p$) model (1) with $p$=1 and $\alpha_1$=1. If $Y_t$ follows a RW, then $Y_t$ is said to be integrated of order 1, or I(1), since we have to apply the difference operator $\Delta$ once to $Y_t$ ($\Delta Y_t = Y_t - Y_{t-1}$) in order to obtain a transformed series which is integrated of order 0, or I(0), i.e. a stationary time series. In general, a time series $Y_t$ is I($d$) if we have to apply $d$ times the difference operator to make it stationary, i.e. $\Delta^d Y_t$ is I(0). In general, the order of integration $d$ of most economic, social-demographic, environmental and climatic variables is taken to be an integer equal to 0, 1 or 2.

The classical distributions which are at the basis of many statistical tests (i.e. t, F, chi-square, etc.) are no longer valid if the series are I($d$), $d$ = 1, 2. At this stage, two questions arise. First, is it possible to test for the order of integration $d$ of a time series? Second, is it possible to use statistical inference with integrated series?

The answer to the first question is given by the tests for the order of integration of a time series (also known as unit-root tests), the most popular of which is the Augmented Dickey-Fuller (ADF)

t-test on the null hypothesis $\rho = 0$ (i.e. $d$ is at least equal to 1) against the alternative hypothesis $\rho < 0$ (i.e. $d = 0$) in the regression model:

$$\Delta Y_t = \rho Y_{t-1} + \Sigma_i \pi_i \Delta Y_{t-i} + v_t \quad (5)$$

$t = 1,\ldots,T$ and $i = 1,\ldots,p$. The ADF test follows a special distribution, known as Dickey-Fuller distribution. The ADF test can be iterated to test any order of integration (on $\Delta^d y_t$), if $d$ is an integer.

The answer to the second question is positive, provided the variables are cointegrated. If $Y_t$ is I(1) and $X_t$ is I(1), $Y_t$ and $X_t$ are said to be cointegrated if a linear combination $c_Y Y_t + c_X X_t$ is stationary, i.e. I(0) for given values of $c_Y$ and $c_X$. Thus there is an equilibrium relationship.

A simple test for cointegration applies ADF to the residuals $\varepsilon_t$ of the regression of $Y_t$ on $X_t$, that is $Y_t = c_X X_t + \varepsilon_t$. Since the residuals are defined as the linear combination between $Y_t$ and $X_t$ with weights $c_Y$=1 and $c_X$ given by the OLS coefficient of $X_t$, if the residuals are I(0) then $Y_t$ and $X_t$ are cointegrated.

The relationship between two variables $Y_t$ and $X_t$, both I(1) and cointegrated, can be represented via an Error Correction Model (ECM), with possible asymmetric terms:

$$\Delta Y_t = \delta + \sum_{i=0}^{s} \alpha_i^+ \Delta X_{t-i}^+ + \sum_{j=0}^{q} \alpha_j^- \Delta X_{t-j}^- + \lambda^+ ECT_{t-1}^+ + \lambda^- ECT_{t-1}^- + u_t \quad (6)$$

where $\Delta X_t = X_t - X_{t-1}$; $\Delta X^+ = \Delta X$ if $\Delta X \geq 0$ and $\Delta X^+ = 0$ otherwise; $\Delta X^- = \Delta X$ if $\Delta X < 0$ and $\Delta X^- = 0$ otherwise; $ECT_t$ are the residuals from the cointegrating regression of $Y_t$ on $X_t$; $ECT^+ = ECT$ if $ECT \geq 0$ and $ECT^+ = 0$ otherwise; $ECT^- = ECT$ if $ECT < 0$ and $ECT^- = 0$ otherwise. Parameters $\alpha^+$ and $\alpha^-$ are the short-run marginal effects, while parameters $\lambda^+$ and $\lambda^-$ are the speeds of adjustment of $Y_t$ from $t$-1 to $t$ to the equilibrium, once a disequilibrium has occurred in $t$-1.

Many economic, socio-demographic, environmental and climatic variables exhibit seasonal behaviour. As in the case of trends, the time series literature distinguishes between deterministic and stochastic seasonality. A non-stationary time series $Y_t$, observed at $S$ equally spaced time intervals per year, is said to be seasonally integrated of order $d$, or SI($d$), if $\Delta_S^d Y_t$ is a stationary and invertible ARMA process of the type described by equations (3) (Ghysels et al., 2003). The simplest seasonal model for non-stationary variables is the seasonal random walk (SRW): $Y_t = Y_{t-S}+\varepsilon_t$. The SRW model can be generalized to the seasonal integrated ARMA (SARIMA) model:

$$\alpha(L)\Delta_S^d Y_t = \theta(L)\varepsilon_t \tag{7}$$

where the polynomials $\alpha(L)$ and $\theta(L)$ in the lag operator $L$ have all roots outside the unit circle, i.e., the AR part of equation (7) is stationary, while the MA part of equation (7) is invertible. An alternative way to model seasonality is via seasonal dummy variables, according to the following basic specification:

$$Y_t = \sum_{s=1}^{S} \gamma_s D_{st} + \varepsilon_t \tag{8}$$

where $D_{st}$ is the seasonal dummy variable which takes the value of 1 when $t$ falls in season $s$. The interpretation of this approach is that seasonality is essentially a deterministic phenomenon, so that the time series of interest is stationary around seasonally varying means. In empirical applications, equation (8) is typically combined with specifications (4) and (6) in order to build up more general and flexible models, which can also be used to produce out-of-sample forecasts of $Y_t$.

## 2.2. Non-parametric forecasting models

Exponential smoothing is a method of adaptive forecasting, which is useful in cases where the number of observations on which to base the forecasts is limited. The basic idea underlying exponential smoothing is that forecasts adjust on the basis of past forecast errors (Mills, 2003). If $Y_t$, $t$=1,...,$T$, is the time series to be forecasted and $Y_t^*$ is the smoothed series, $Y_t^*$ is calculated according to the following recursive model:

$$Y_t^* = \alpha Y_t + (1-\alpha)Y_{t-1}^* \tag{9}$$

where $0<\alpha\leq 1$ is the smoothing factor. The smaller is α, the smoother is $Y_t$. Model (9) is referred to as single smoothing, and is appropriate for stationary, non-seasonal time series. By repeated substitutions in (9), $Y_t^*$ can be written as a weighted average of past values of $Y_t$, where the weights $(1-\alpha)^t$ decline exponentially with time. The out-of-sample forecasts from single smoothing are constant for all observations and are given by: $Y_{T+h}^* = Y_T$, for all $h$>0.

The method known as double smoothing applies single smoothing twice and is appropriate for time series which are non-stationary for the presence of a linear deterministic trend. The model is given by the following two recursive equations:

$$\begin{aligned} Y_t^* &= \alpha Y_t + (1-\alpha)Y_{t-1}^* \\ Y_t^{**} &= \alpha Y_t^* + (1-\alpha)Y_t^{**} \end{aligned} \tag{10}$$

where $Y_t^{**}$ is the double smoothed series. Forecasts from double smoothing are calculated as:

$$Y_{T+h}^{**} = 2Y_T^* - Y_T^{**} + \alpha(Y_T^* - Y_T^{**})h/(1-\alpha) \tag{11}$$

Equation (11) suggests that $Y_{T+h}^{**}$ lies on a linear trend with intercept $2Y_T^{*}-Y_T^{**}$ and slope $\alpha(Y_T^{*}-Y_T^{**})/(1-\alpha)$.

A method which is suitable for a time series with a linear trend and additive seasonal variations is the so-called additive Holt-Winters. The smoothed series is given by:

$$Y_{t+h}^{*} = a + bh + c_{t+h} \tag{12}$$

where $a$ and $b$ are the permanent component and trend parameters, while $c_{T+h}$ represent the additive seasonal factors. The coefficients are specified according to the following expressions:

$$\begin{aligned} a(t) &= \alpha(Y_t - c_t(t-s)) + (1-\alpha)(a(t-1)+b(t-1)) \\ b(t) &= \beta(a(t)-a(t-1)) + 1 - \beta b(t-1) \\ c_t(t) &= \gamma(Y_t - a(t+1)) - \gamma c_t(t-s) \end{aligned} \tag{13}$$

where $\alpha$, $\beta$ and $\gamma$ are the smoothing parameters and $s$ is the seasonal frequency. Forecasts are computed as:

$$Y_{T+h}^{*} = a(T) + b(T)h + c_{T+h-s} \tag{14}$$

If $Y_t$ is a time series characterized by the presence of a linear trend and multiplicative seasonal variability, the multiplicative Holt-Winters model is typically applied. In this case, the smoothed series is given by the following modified version of (12):

$$Y_{t+h}^{*} = (a + bh)c_{t+h} \tag{15}$$

the evolution of the coefficients $a$, $b$ and $c_t$ being given by slightly modified versions of equations (13).

## 2.3. Panel data and spatial models

Many economic, socio-demographic, environmental and climatic variables are observed through time ($t$=1,...,$T$) and across "individuals" ($i$=1,...,$N$), where the notion of "individual" used in the present context is broad enough to embrace real individuals, households, countries, geographical areas, firms, economic sectors, etc. A variable observed through time and across individuals, $Y_{it}$, is said to have a panel data structure (Baltagi, 2001).

Modern econometrics and statistics distinguish between two broad classes of static models for panel data, fixed effect and random effects models. Although both approaches share the same idea of taking into account one major feature of panel data, namely individual heterogeneity, they provide radically different ways of modelling individual variability. The fixed effects model assumes that individual heterogeneity can be represented via individual-specific constants, as:

$$Y_{it} = \alpha_i + \sum_{r=2}^{K} \beta_r X_{rit} + u_{it} \qquad (16)$$

where $u_{it}$ is a classical error term. This model is appropriate if individual heterogeneity is systematically distributed among individuals, i.e. the sample of data is non-random. Since individual heterogeneity is represented by the additional regressors $\alpha_i$, correlation between explanatory variables $X_{it}$ and individual heterogeneity is allowed for in the fixed effects model. On the contrary, the random effects model assumes that individual heterogeneity is randomly distributed among individuals, hence it has to be represented as a classical random normal variable $\mu_i$, which contributes to a composite error term, $v_{it}$:

$$Y_{it} = \alpha + \sum_{r=2}^{K} \beta_r X_{rit} + v_{it} \ , \ v_{it} = \mu_i + u_{it} \tag{17}$$

OLS is consistent for the parameters $\beta_r$, $r = 2,\ldots,K$, of model (16), while GLS is consistent for the parameters in model (17). Since individual heterogeneity is part of the model error term in equation (17), correlation between individual heterogeneity and the explanatory variables $X_{it}$ would lead to inconsistent estimates.

In applied statistics the autocorrelated structure of many time series variables is widely acknowledged. The simplest way to allow for data autocorrelation is to extend model (17) to include the lagged dependent variable as an additional regressor (dynamic panel data models). Unfortunately, the lagged dependent variable is correlated with the composite error term $v_{it}$, leading to inconsistency of the LS estimators. This inconsistency is still present if the variables involved in model (17) are transformed in first differences, in order to eliminate the random effects $\mu_i$:

$$\Delta Y_{it} = \gamma \Delta Y_{it-1} + \sum_{r=2}^{K} \beta_r X_{rit} + u_{it} \tag{18}$$

Equation (18) is typically estimated with instrumental variables techniques (e.g. Anderson-Hsiao and Arellano-Bond estimators).

When sample data have a natural location component, two problems arise, namely spatial heterogeneity and spatial dependence (see Anselin, 1988; for an introduction to spatial econometric models see, among others, Cattaneo, 2008 and Cattaneo et al., 2010). Spatial heterogeneity (SH) refers to the fact that many phenomena lead to structural instability over space, in the form of different response functions or systematically varying parameters. SH induces familiar problems such as heteroskedastic random coefficient variation and switching regressions. Spatial dependence (SD) occurs when sample data observations exhibit correlation with reference to points or location in space. Formally, one observation associated with a location $i$ depends on other observations at locations $j$, $j \neq i$, that is $Y_i = f(Y_j)$, $i=1,\ldots, N$; $j \neq i$. In general, the dependence is among several observations, as the index $i$ can take on any value from $i=1,...,N$.

Two reasons are commonly given to explain SD. First, data collection of observations associated with spatial units might reflect measurement errors. Second, the spatial dimension of socio-demographic, economic or regional activities (e.g. environment and climatic variables) may be an important aspect of a modelling problem.

In spatial data analysis the spatial structure of the observations is made explicit by means of spatial weight matrices. The elements of the weight matrix are non-stochastic and exogenous to the model and derived from alternative criteria, such as contiguity (neighbouring units should exhibit a higher degree of spatial dependence than units located far apart), Cartesian space (physical distance matters), non-geographic factors (economic/social proximity).

The presence of spatial correlation between the units of observations can be detected by means of tests which capture the extent to which values similarity matches with locations similarity. In this context, positive spatial correlation exists if likewise values tend to cluster in space; negative correlation exists if the locations are surrounded by neighbour with dissimilar values; zero spatial correlation implies that it is not possible to identify a specific spatial pattern of values. This situation is also described as spatial randomness, as values observed at a location do not depend on values observed at neighbouring locations.

A fairly general spatial econometric model contains both a spatial lagged dependent variable and a spatially autocorrelated error term, and can be written, using matrix notation, as:

$$\begin{aligned} Y &= \rho W_1 Y + X\beta + U \\ U &= \lambda W_2 U + E \\ E &\sim N(0, \sigma^2 I_N) \end{aligned} \tag{19}$$

However, model (19) is rarely used in practice, because there are problems of identification whenever $W_1$ equals $W_2$. If $W_2$=0 in specification (19), the so-called spatial lag (SL) model is obtained, whereas the spatial error (SE) model originates when $W_1$=0 in (19). The SL model is appropriate when the focus of interest is the assessment of the existence and strength of spatial interactions, whose existence is directly derived from an economic model. SD in the SE model is

referred to nuisance dependence. This model is appropriate when the concern is with correcting for the potentially biasing influence of the spatial autocorrelation, due to the use of spatial data, irrespective of whether the model is spatial or not.

The reduced form of the SL model is:

$$Y = (I_N - \rho W_1)^{-1} X\beta + (I_N - \rho W_1)^{-1} E \tag{20}$$

where $(I_N - \rho W_1)^{-1}$ is a full matrix, which induces error terms in all locations. The estimation method of the SL model is 2SLS or ML. The spatial lag term $W_1 Y$ in equation (19) yields a measure of spatial dependence that controls for the effect of the included exogenous variables. It indicates the effects of spatial autocorrelation after controlling for other variables. On the contrary, OLS is unbiased for the SE specification, although it is an inefficient estimator, since it ignores the specific variance structure for the errors

# 3. Modelling the relationship between climate change and health. What does the literature say?

## 3.1. Quantitative studies

### 3.1.1. Primary studies

*Time series models* have been used extensively for predicting the evolution pattern of diseases, and more specifically to assess the relationship between environmental exposure and mortality or morbidity over long time periods. These predictions are a necessary step for quantifying potential impact of climate on health and the related costs. In the field of climate based Early Warning Systems (EWS), which are used to predict the occurrence of epidemics of infectious diseases, Chaves and Pascual (2007) review and compare linear and non-linear models for forecasting

seasonal time series of diseases. Using American cutaneous leishmaniasis, as an example, the models are evaluated based on the predictive R2 for forecasting the data "out-of-fit". Seasonal autoregressive models that incorporate climatic covariates are found to provide the best forecasting performance. Additionally, a bootstrapping experiment shows that the relationship of the disease time series with the climatic covariates is strong and consistent for the seasonal autoregressive (SAR) modeling approach. While the autoregressive part of the model is not significant, the exogenous forcing due to climate is always statistically significant. Prediction accuracy can vary from 50% to over 80% for diseases burdens at time scales of one year or shorter.

A different strategy for predicting the pattern of diseases is given by Medina et al. (2007), who investigate the dynamics of diarrhea, acute respiratory infection (ARI), and malaria in Niono, Mali. The authors observe that these disease time-series often *i)* suffer from non-stationarity; *ii)* exhibit large inter-annual plus seasonal fluctuations; and, *iii)* require disease-specific tailoring of forecasting methods. To accommodate these characteristics they suggest using a non-parametric technique, the multiplicative Holt-Winters method (MHW). This is a recursive method that can be described as follows: *i)* based on past information and pseudo-parameters initialization the MHW produces point forecasts (the method also decompose the time series into level, trend (rate of change), seasonal, and approximately serially uncorrelated residual TS components); *ii)* point forecasts are recursively revised through residuals bootstrap to produce median forecasts and their 95% confidence interval bounds; *iii)* these median forecasts and contemporaneous time-series information is used by the MHW program to update the forecasts and prediction interval bounds. Step *i)* also decompose the time series (TS) into level, trend (rate of change), seasonal, and approximately serially uncorrelated residual TS components.

Using longitudinal data from 01/1996 to 06/2004 the authors find that the MHW produces reasonably accurate median 2- and 3-month horizon forecasts for the considered non-stationary time-series, i.e., 92% of the 24 time-series forecasts generated (2 forecast horizons, 3 diseases, and 4 age categories = 24 time-series forecasts) have mean absolute percentage errors about 25%. In their experiments the MAPE is smaller for the forecasts of monthly consultation rates for malaria and ARI, while the accuracy decreases for diarrhea's consultation rates.

Other time series approaches have been used to explore the issue of extreme climatic events' impacts. Curriero et al. (2002) perform time series analyses to estimate the temperature-mortality association for eleven eastern US cities from 1973 to 1994. By using log-linear models for time series data the authors find the following evidences: *i)* current and recent days' temperature are the weather factor most strongly predictive of mortality; *ii)* it appears to exist a threshold temperature

below which mortality tends to decrease as temperatures increases form the coldest days, and above which mortality risk increases as temperature increases; *iii)* a strong association exists between mortality associated to extreme temperatures and latitude.

Shakoor et al. (2006) use time-series models to analyze mortality due to thermal stresses during heat waves compared to total mortality occurring throughout the whole summer, to understand what fraction of the total impact is attributable to temperature extremes. In the same context, Keatinge et al. (2000) estimate the heat-related mortality due to climate change in Europe, using time-series data and taking into account the threshold temperature where mortality is lowest. The findings suggest that European population have adapted to average summer temperatures, and might adapt to future higher temperatures with only a minor increase in heat-related deaths. These studies suggest that the process of acclimatization should be taken into account when assessing the impact of heat waves and increased temperatures.

Finally we mention Rodó et al. (2002) who present a time-series analysis of the relationship between El Niño/Southern Oscillation (ENSO) and the prevalence of cholera in Bangladesh using mortality data recorded on a monthly period from 1893 to 1940. Singular spectrum analysis (SSA) is used to capture discontinuous dynamics and trends. The technique allows to decompose the irregular dynamics of the time series and to isolate the inter-annual variability of the data. Their findings suggest that ENSO is responsible for more than 70% of the dynamics of the disease, this relationship being discontinuous in time.

### 3.1.2. Secondary studies

*Cross-section and panel data models*

A subject that is contiguous but relevant for the impact of climate on health and its ethical implications is the relationship between pollution and income. Rupasingha et al. (2004) use and extended spatial econometric analysis to investigate whether it exists an inverse-U relationship between various pollution indicators and county per capita GDP in the US (the so-called environmental Kuznets curve, EKC). The authors emphasize that the EKC is conditional on various structural features (e.g. technology, education, political practices) of each locality. Moreover, they expand the analysis including ethnic diversity among the covariates and by controlling for spatial dependence. Their initial results support the existence of the EKC relationship. The inclusion of spatial autocorrelation is found to raise the turning point of the curve. Another result is that more

ethical diverse counties are more polluted. Finally, incorporating a cubic term for income, they find that the toxicity index eventually increases again as income continues to rise.

Salomon and Murray (2002) analyze the patterns of diseases and mortality rates in the framework of the literature on epidemiologic transition (Omran, 1971). The authors provide a cause-of-death analysis for WHO data on mortality by age and sex and recorded cause by 1950 to 2002, and use models for compositional data. Specific causes of death are modeled as a function of the overall level of mortality and the income per capita. The findings suggest that considerable variations in cause-of-death patterns across countries and over time are coupled with empirical regularities. Indeed, as mortality levels declines the composition of the causes changes. The effects of mortality declines are more noticeable for children and young adults (with a shift from Group 1 diseases - infectious and parasitic diseases, respiratory infections, maternal conditions, etc. - to Group 2 diseases - diabetes, endocrine disorders, etc. - and Group 3 - injuries - in proportions that vary according to age and sex). In older adults, the composition of mortality remains stable while deaths shift to older ages. Moreover, in many societies, "protracted and polarized" epidemiologic transitions reflect heterogeneity of the social strata.

*General equilibrium models*

General Equilibrium models have been used to estimate the welfare costs (or benefits) of health impacts of climate variables.

Martens (1998a) conducts first a meta-analysis of aggregated effects of a change in temperature on mortality for total, cardiovascular and respiratory mortality. Second, he combines these effects with projections of changes in baseline climate conditions of 20 cities, according to climate change scenarios of three General Circulation Models (GCMs). The author finds that for most of the cities included, global climate change is likely to lead to a reduction in mortality rates due to decreasing winter mortality. This effect is most pronounced for cardiovascular mortality in elderly people in cities which experience temperate or cold climates at present.

Similar to Martens (1998a), Tol (2002) consider GCM (General Circulation Models) based studies' results to estimate (and evaluate in monetary terms) the impacts of climate change for a wide range of market and non-market sectors (agriculture, forestry, water, energy, costal zones and ecosystems, as well as mortality due to vector-borne diseases, heat stress and cold stress). The author estimates that small increases in temperatures would bring some benefits (mainly for the developed world). The conclusion on the global impact of climate change depends crucially on the weights used to

aggregate the regional values. Using the simple sum the benefits amount to 2% of GDP. Considering globally averaged prices to value non-markets goods the impact is a 3% reduction of global income. According to equity (ratio of global to regional per capita income) - weighted results the world impact is null. Global impacts become negative beyond 1°C increase in temperatures.

Bosello et al. (2006) make use of the General Equilibrium Model (GTAP) in an unconventional approach in order to analyse how health impacts would affect the general economy. Their aim is to estimate the indirect costs on the economic system derived from the health effects as a result of an increase of one degree Celsius in global mean temperature. They estimate the impact on labour productivity and health care expenditures for both the public system and private households, as well as the impacts on GDP. Six health outcomes are considered (cardiovascular disease, respiratory disease, diarrhoea, malaria, dengue and schistosomiasis). The impacts on health are taken from different studies (Tol, 2002; Martin and Lefebvre, 1995; Morita et al., 1994) that estimate the change in mortality due to an increase of one degree in the global mean temperature. Using data of GTAP model of Hertel and Tsigas (2002) and IMAGE team (2001) (see the paper and the references therein for a more accurate description) the authors find an increase in mortality and morbidity due to respiratory illness, malaria, dengue fever and diarrhoea, with increased costs of illness. In contrast, they evidence a decrease in cardiovascular diseases and schistosomiasis, which dominate the overall impact, leading to a negative trend in the additional expenditure for health care in all countries.

Although the results of Bosello et al. (2006) go on the same direction (but with stronger evidence) as the conclusions of earlier papers (e.g. Martens, 1998a; and Tol, 2002), they are controversial. Indeed, Ackerman and Stanton (2006) challenge Bosello et al. (2006), Martens (1998b) and Tol (2002). The authors argue that Bosello et al. (2006) results are biased due to the omission of extreme weather events and human adaptation to gradual temperatures changes. The main concern is about the use of average temperatures instead of increased variability in local temperatures, which results in an increase of the frequency of extreme hot or cold. Another important issue to be considered in this context is related to the population expected to support heat- and cold-related stresses. In Bosello et al. (2006), as well as in Tol (2002), heat stresses are assumed to impact the urban population only, while cold-related diseases are expected to occur in both the rural and urban population. This assumption might have a strong influence on final results and needs therefore to be further analyzed, especially when considering countries with large rural population (De Dube et al., 2005).

As seen above Bosello et al. (2006) and Ackerman and Stanton (2006) find contrasting evidence, which is partly related to whether or not extreme climatic events are considered. This suggests that what projected changes in temperatures are considered has a big impact on the results. A review of main findings of the economic literature on climate effects is given as a part of the research of Stern (2007). Also an advance in this field of research and modeling is given by the author (see next section for a review on the Stern Report).

### 3.1.3. Comparative risk analyses

Using comparative risks assessments (CRA), which integrate climate models and the evaluation of the health effects of rising temperatures, Ezzati et al. (2003) estimate the potential gains that would derive from combined preventive measures. The authors provide an estimation of the joint effects of 20 selected leading risk factors in 14 epidemiological sub-regions (as a proxy of the world). Among the major risk factors they include environmental risks (such as unsafe water, sanitation and hygiene) that are correlated with the climate. As a tool for the estimation they define the potential impact factor (PIF) as the reduction in population diseases burden or mortality that would occur if the current exposures to multiple risk factors were reduced to an alternative exposures distribution (see the article for a formal definition of the PIF). They find that globally 47% of premature deaths and 39% of total disease burden in 2000 resulted from the joint effects of the considered risk factors. Their results suggest that joint actions would result in a massive reduction of death due to the burden of diseases. Moreover, they find evidence that reducing multiple major risk factors would decrease some of the differences between regions.

McMichael et al. (WHO, 2003) provide projections of relative risk attributable to climate change under alternative exposure scenarios, using global climate models and comparative risk assessment. The results are presented for broad WHO geographical regions, and include malaria, diarrhea, malnutrition and heat-related stresses. The study presents some limitations which should be investigated in future research in order to estimate the burden of disease. The issue of improved access to water and sanitation systems is not considered, nor is the level of economic development, although these are important factors influencing the population vulnerability. A second limitation is that the correlation between different health outcomes is not evaluated. This is particularly important for malnutrition which is strictly related to occurrence of other diseases. Finally, the model for malaria relates climate variables to geographical areas at risk (and population), instead of

disease incidence, and estimates the impacts related to changes in the average temperature while not accounting for climate variability.

In the same field of research as Ezzati et al. (2003), Kovats et al. (2005) use comparative risk assessment (CRA) techniques to quantify the avoidable deaths and diseases.[2] The authors consider the WHO 2004 estimates and remark that to generate consistent estimates the models need to incorporate: geographical variation in the vulnerability to climate; future changes in the disease rates due to factors other than climate (e.g. decreases rates of infectious diseases due to technological advances); assumptions on a country's ability to control a disease such as malaria, dengue fever or diarrheal disease; uncertainties around the exposure-response relationship. Moreover, they claim that even controlling for the above mentioned (potentially positive or negative) issues, no model can take into account the possibility of irreversibility or plausible low probability events with potentially high impact on human health. As a main consequence, threshold health effects to regulate "tolerable" amount of climate change cannot be identified.

Finally, Hijioka et al. (2002) relate water-borne diseases with temperature in 14 world regions, showing that the disease incidence tends to increase with temperature. They use multiple regression analysis and include the effect of water supply and sanitation coverage, annual average temperature and per capita GDP, taking into account different IPCC climate scenarios. The results show large regional differences in the impacts.

[2] The comparative risk assessment approach has been developed in the late 90s by the WHO with aim of estimating the contribution of that different public health factors make to the global burden of diseases. The CRA is based on the following data for each risk factor: *i)* the current and predicted risk distribution of the risk factor; *ii)* the exposure-response relationship of the associated disease; *iii)* the total burden of diseases (e.g. DALYs) lost to the various diseases associated with the risk factor. The proportion of the total burden of a disease that is attributable to e specific risk factor is called Impact Fraction and is defined as:

$$IF = \frac{\sum P_i RR_i - \sum P_i^{'} RR_i}{\sum P_i RR_i}$$

where $P_i$ is the proportion of population in the exposure category, $P_i^{'}$ is an alternative proportion and $RR_i$ is the relative risk exposure at category *i* compared to the reference level.

## 3.2. Focus: quantitative studies of the relationship between climate change and malaria

### 3.2.1. Time series studies

Various time series studies explore the relationship between average temperatures, mid-night temperatures, temperatures in conjunction with rainfall rates, as well as November and December temperatures on malaria. In particular, Freeman and Bradley (1996), Freeman (1995), Tulu (1996), Loevinsohn (1994), Bouma et al. (1996) find a significant impact of climate on malaria in Zimbabwe, the Debre Zeit sector of Ethiopia, Rwanda, and the Northwest Frontier Province in Pakistan, respectively. December temperatures coupled with humidity are used by Bouma et al. (1996) to predict incidence rates of malaria in Pakistan. Other studies consider temperature and deforestation in Tanzania (Matola et al., 1987) and Kenya (Malakooti et al., 1997). According to the latter study forest clearing has been the cause for increases in malaria transmission. Kenya is considered also by Patz et al. (1998). The main findings of the article are that soil moisture correlates with the human-biting rate of mosquito vectors with a two-week delay. Also soil moisture and entomological inoculation rate[3] are related, with infective parasites taking a six-week time to develop.

It has been hypothesized that increasing temperatures could be part of the reason why malaria can now survive at higher altitudes. Many other confounding factors, however, could be causing the increase in malaria in these areas (Patz and Lindsay, 1999). The dynamics of the geographical spread of malaria are analyzed by Pascual et al. (2006). The authors focus on the most important malaria species for humans, *Plasmodium falciparum* and *Plasmodium vivax*, whose range is limited at high altitudes by low temperatures. They investigate whether global warming could drive the geographical spread of the disease and produce an increase in incidence at higher-altitude sites. They use data for four high-altitude sites in East Africa in from 1950 to 2006. A nonparametric analysis that decomposes the variability in the data into different components is performed and reveals that the dominant signal in three of the sites and the subdominant signal in the fourth one correspond to a warming trend. To assess the biological significance of this trend, the authors drive a dynamical model for the population dynamics of the mosquito vector with the temperature time series and the corresponding detrended versions. This approach suggests that the observed

[3]Entomological inoculation rate is the product of the human-biting rate and the proportion of female mosquitoes carrying infective parasites in their salivary glands ready to be delivered to the next host.

temperature changes would be significantly amplified by the mosquito population dynamics with a difference in the biological response at least one order of magnitude larger than that in the environmental variable. By using parametric models they also find the existence of significant (linear) trends.

Shanks et al. (2002) investigate whether the reemergence of malaria in Western Kenya could be attributed to changes in meteorological conditions. The existence of trends in a continuous 30-year monthly malaria incidence dataset (1966–1995) is tested for. Malaria incidence increased significantly ($p=0.0133$) during the 1966–1995 period. In contrast, no aspect of climate is found to have changed significantly-neither the temperature extremes (maximum and minimum) nor the periods when meteorological data were transformed into months when malaria transmission is possible. Therefore, the authors conclude that climate changes have not caused the highland malaria resurgence in western Kenya. Moreover they suggest that two other factors may have influenced the increase in malaria hospitalizations: an increase in malaria severity indicated by an increased case-fatality rate (from 1.3% in the 1960s to 6% in the 1990s) that is most likely linked to chloroquine resistance. Secondly, travel to and from the Lake Victoria region by a minority of the tea estate workers also exerts an upward influence on malaria transmission in Kericho, Kenya, since such travel increases the numbers of workers asymptomatically carrying gametocytes, which infect.

### 3.2.2. Cross-section and panel data analyses

The spatial variation of malaria is analyzed by Kazembe et al. (2006), who examine malaria-related hospital admissions and in-hospital mortalities among children in Africa. The authors apply spatial regression models to quantify the spatial variation of the two outcomes. Using pediatric ward register data from Zomba district, Malawi, between 2002 and 2003, as a case study, they develop two spatial models. The first is a Poisson model applied to analyze hospitalization and minimum mortality rates, with age and sex as covariates. The second is a logistic model applied to individual level data to analyze case-fatality rate, adjusting for individual covariates. The results show that rates of hospital admission and in-hospital mortality decrease with age. Case fatality rate is associated with distance from the hospital, age, wet season, and increases if the patient is referred to the hospital from the primary health facilities. Furthermore, death rates are high on the first day, followed by relatively low rates as the length of hospital stay increases. The outcomes show substantial spatial heterogeneity, which may be attributable to the varying determinants of malaria risk, health services availability and accessibility, and health seeking behavior. Moreover, the increased risk of mortality of referred children may imply inadequate care being available. The authors suggest that reducing the burden of malaria requires integrated strategies that encompass

availability of adequate care at primary facilities, introduce home or community case management and encouraging early referral. Those interventions would be needed to interrupt malaria transmission.

In a subsequent article, Kazembe (2007), the author extends the analysis of Kazembe et al. (2006) to profile spatial variation of malaria risk and analyze possible association of disease risk with environmental factors at sub-district level in northern Malawi. Using the same data on malaria incidence the author compares Bayesian Poisson regression models assuming different spatial structures. For each model he adjusts for environmental covariates initially identified through bivariate non-spatial models. The model with both spatially structured and unstructured heterogeneity is shown to provide the best fit, based on models comparison criteria. Malaria incidence appears to be associated with altitude, precipitation and soil water holding capacity. The risk increases with altitude (relative risk (RR): 1.092, 95% interval: 1.020, 1.169) and precipitation (RR: 1.031, 95% interval: 0.950, 1.120). At medium level of soil water holding capacity relative to low level, the risk is reduced (RR: 0.521, 95% interval: 0.298, 0.912), while at high level of soil water holding capacity relative to low level the risk is raised (RR: 1.649, 95% interval: 1.041, 2.612). Compared to the commonly used standardized incidence ratios, the model-based approach appears to provide homogenous and easy to interpret risk estimates. Generally, the smoothed estimates show less spatial variation in risk, with slightly higher estimates of malaria risk (RR > 1) in low-lying areas mostly situated along the lakeshore regions, in particular in Karonga and Nkhatabay districts, and low risk (RR < 1) in high-lying areas along Nyika plateau and Vwaza highlands. The results suggest that the spatial variation in malaria risk in the region is a combination of various environmental factors, both observed and unobserved. The results also identify what are the areas of increased risk, where further epidemiological investigations could be carried out.

Another interesting study in this context is the one of Bhattacharya et al. (2006) who project malaria transmission in new geographical regions in India. According to this study malaria is expected to move from central regions towards South Westerns and Northern Regions by 2050. Some studies about malaria also project a shift in the duration of transmission windows which might increase or decrease according to the different climatic conditions of a region (Bhattacharya et al., 2006; Dhiman et al., 2008).

Lindsay and Martens (1998) consider the progressive rise in the incidence of malaria over the last decades in African highlands. The phenomenon is largely a consequence of agroforestry development, and is exacerbated by scarce health resources. Moreover, in these areas where the pattern of malaria is unstable, epidemic may be precipitated by relative subtle climate changes and

therefore requires special monitoring. The authors use mathematical models to identify epidemic-prone regions in highlands Africa, and to quantify the difference expected to occur as a consequence of projected global climate change. To make estimates about the areas that are vulnerable to epidemic outbreaks of malaria, they use data and models from Geographic Information Systems (GIS) (computerized mapping systems) and Remotely Sensed (RS) imagery data from earth-orbiting satellites. Correlations among variables are found. However, the authors observe that since correlation doesn't imply causality these results are not conclusive and require further investigation. To model the dynamics in highlands malaria in relation to climate change they use an integrated system, scenario-based approach (Integrated Assessment Models, see among others, Martens, 1998b and Stern, 2007). Evidence is found that the direct influence of climate may contribute to malaria risk. However, this effect cannot be claimed to be the be the most important determinant of malaria transmission. The effects of temperature on mosquito development, feeding frequency, longevity and incubation period are estimated. The model is linked to baseline climatology data from 1931 to 1960 and uses integrated techniques to generate climate scenarios. Their findings suggest that is not possible to prove that any single factor has caused the outbreaks in African highland. Projected climate changes are likely to modify the epidemics in the regions: 260–320 million more people are projected to be affected by malaria by 2080 as a consequence of new transmission zones.[4]

### 3.2.3. General equilibrium models

Martens (1998a) proposes a system-oriented analysis, based of scenarios of projected temperatures, and that considers joint effects (rather then phenomena in isolation) to assess the future impacts of climate change. In his analysis he considers the effects of climate change on vector-borne diseases, on thermal-related mortality, and the effects of increasing ultra-violet levels due to ozone depletion on skin cancer. Considering malaria the author defines the basic reproduction rate in an area ($R_0$) as the vector capacity multiplied by the duration of the infectious period in humans. The factors that are involved in the calculation of ($R_0$) include: the mosquitoes/people ratio, the number of mosquito bites per person per day, the probability that an infected mosquito infects a human, the chances that

[4] The study of Lindsay and Martens (1998) as well as Shanks et al. (2002) and Pascual et al. (2006) analyze the (re)emergence of malaria in regions once free of this disease risks. These contribution add to a vast literature on the epidemics of malaria. This includes: studies of the highlands of Kenya, Madagascar, Burundi and Irian Jaya, Indonesia (Kigotho 1997; Khaemba et al., 1994; Fontaine et al., 1961; de Zulueta, 1994; Fontenielle et al., 1990; Mouchet et al., 1997; Marimbu et al., 1993; Anthony et al., 1992; Bangs et al., 1995). Other analyses include the study of Freeman (1994) and Woube (1997) on epidemics in Manyuchi dam, Zimbabwe and Ethiopia, respectively.

a mosquito becomes infected during a blood meal, the incubation period, and the daily survival probability of the mosquito. Indirect factors that affect the ones that are listed above include: the availability of breeding sites which is related to precipitation, human population density, human population migration, the feeding habits of the mosquitoes, the presence of other animals on which the mosquitoes feed, human exposure which can be affected by the use of bednets or other interventions, temperature the immunological and nutritional status of the population, the effectiveness of medical treatment, natural enemies of the mosquitoes, and control efforts. This model is further complicated by algorithms that predict changing genetic adaptations in the parasite and vector that lead to resistance. Based on this approach, evidence is found that the number of people in developing countries likely to be at risk of malaria infection will increase by 5-15% because of climate change, depending on which the Global Circulation Model (GCM) and climate change scenario is used. The areas that are expected to have the most increase in malaria transmission are ones at the fringes of transmission. Unless they are able to use effective control strategies, these regions have low levels of immunity and are likely to experience epidemics (Martens, 1998a).

In general, there is considerable uncertainty about the magnitude of the overall impact of malaria. While some models project a net increase in the population exposed to malaria (and in the incidence rate) due to climate change (Martens et al., 1995), others have found only minor changes in malaria distribution (WHO, 2003 - McMichael et al.). This uncertainty is due to the complex dynamics underlying the transmission of this vector and to other important factors such as the socio-demographic and environmental factors which are playing a substantial role in the transmission mechanism.

## 3.3. General studies

The previous section has concentrated on recent quantitative contributions on the relationship between climate and health. Since this issue involves many disciplines and view points, however, more extensive outlooks become necessary, as they provide a framework for understanding the interactions between climate and health in a broader perspective. A summary of the main reports and of the specific findings and methods therein is presented below.

### 3.3.1. The economics of climate change

The Stern Report (2007) is a key reference giving a complete framework of the economics of climate change. The book reviews scientific and geological basis of the studies on climate change's impacts. For example, it lists the possible impacts associate to 1°, 2° up to 5°C of temperatures increases. Restricting to the effects for health, these include a larger (and increasing exponentially with temperatures) number of deaths caused by diseases such as malaria, diarrhea and malnutrition at lower latitudes (Africa); and a reduction in winter deaths at higher latitudes (Northern Europe, USA). The author considers the ethical implications of the disproportionate distributions of impacts across regions and populations, and provides a series of policy indications. For the problem at stake, the chapter that concerns the economic analyses of climate change costs is specifically relevant.

The measurement of costs of climate (measured on income/consumption, health and environment dimensions) is a challenging task. The main reasons being that this kind of analyses involves the use of variables and projections that are highly uncertain (however, according to the author, omitting some of uncertain but potentially most damaging impacts have caused some early attempts to underestimate the costs of climate change). Moreover, the effects can be seen only over several decades and with a long-time delay. Based on a review of the studies of the costs of climate warming, the author concludes that the Integrated Assessment Models (IAM) constitute a valid methodological foundation; however first-round IAM studies consider the effects of climate at temperatures that are now likely to be exceeded. The mixed evidence found by different authors crucially relies on what increase in temperature is considered. Indeed, there is a common evidence that the warming above 3-4°C would reduce global welfare, and that and temperatures increases of 5-6°C can be estimated to be equivalent to a 5%-10% reduction in global GDP in the "no-climate-change" scenario.

In the methodological framework of IAM, Stern estimates the BAU (business as usual) costs of climate: he estimates the costs to be equivalent of a per-capita reduction of income of 5% at minimum. This proportion could increase to 11% by considering the direct effects on environment and health ("non-market" impacts).[5] In case it turns out to be true that the responsiveness of climate system to gas emissions is larger than what previously thought, the costs would increase even more. Finally there is a noticeable disproportion in the distribution of the burden of climate change impact among developing and rich countries. As regards health, the major impacts are expected in

[5] The total damage evaluated in terms of loss of life caused by climate change is estimated to range from US$ 6 billion to US$ 88 billion (1990 dollar prices) (IPCC, 2007). In terms of disability adjusted life years (DALYs) the loss has been estimated around 5.5 million in year 2000 (Lancet and the University College London Institute for Global Health Commission, 2009).

countries such as Sub-Saharan Africa and Asia, which are already facing a considerable burden of disease. Developing countries are actually tackling with more constraints. On the one hand they are expected to face high population growth with increased risk of poor housing, hunger and infectious diseases due to poor water and sanitation systems. On the other hand, their adaptive capacity is limited in terms of financial and infrastructural resources, health care system, poor health status of the population and poor capacity of collecting and analyzing data. Additional problems are related to income inequalities, migration and conflicts. As stated in the last IPCC report (IPCC, 2007), priorities for research should include the development of methods to provide more quantitative assessments of climate change impacts in low- and middle-income countries.

### 3.3.2. Managing the health effects of climate change

Managing the Health Effects of Climate Change is a wide multidisciplinary overview of the major threats - both direct and indirect - to global health from climate change, carried on by Lancet and University College London Institute for Global Health Commission (2009). Effects of predicted climate change are described by the authors and actions to be undertaken are discussed.

The starting point of the analysis is that during this century, earth's average surface temperature rises are likely to exceed the safe threshold of 2°C above preindustrial average temperatures. Rises will be greater at higher latitudes, with medium-risk scenarios predicting 2–3°C rises by 2090 and 4–5°C rises in northern Canada, Greenland, and Siberia.

Health effects of the predicted climate change will cause vector-borne diseases to expand their reach and death tolls, especially among elderly people, moreover the indirect effects of climate change on water, food security, and extreme climatic events are likely to have the biggest effect on global health.

An integrated and multidisciplinary approach to reduce the adverse health effects of climate change requires at least three levels of action. First, policies must be adopted to reduce carbon emissions and to increase carbon biosequestration, and thereby slow down global warming and eventually stabilize temperatures. Second, further research is needed to understand clearly the links between climate change and disease occurrence. Third, appropriate public health systems should be put into place to deal with adverse outcomes in terms of efficient and cost-effective adaptation measures at local, and national levels.

The UCL Lancet Commission considers what the main obstacles to effective adaptation might be, focusing on six aspects that connect climate change to adverse health outcomes: changing patterns of disease and mortality, food, water and sanitation, shelter and human settlements, extreme events, and population and migration. Each is considered in relation to five key challenges to form a policy response framework: informational, poverty and equity-related, technological, sociopolitical, and institutional.

Our capacity to respond to the negative health effects of climate change relies on the generation of reliable, relevant, and up-to-date information. Strengthening informational, technological, and scientific capacity within developing countries is crucial for the success of a new public health movement. This capacity building will help to keep vulnerability to a minimum and build resilience in local, regional, and national infrastructures.

Few comprehensive assessments on the effect of climate change on health have been completed in low-income and middle-income countries, and none in Africa. The report endorses the 2008 World Health Assembly recommendations for full documentation of the risks to health and differences in vulnerability within and between populations; development of health protection strategies; identification of health co-benefits of actions to reduce greenhouse gas emissions; development of ways to support decisions and systems to predict the effect of climate change; and estimation of the financial costs of action and inaction. Policy responses to the public health implications of climate change will have to be formulated in conditions of uncertainty, which will exist about the scale and timing of the effects, as well as their nature, location, and intensity.

A key challenge is to improve surveillance and primary health information systems in the poorest countries, and to share the knowledge and adaptation strategies of local communities on a wide scale. Essential data need to include region-specific projections of changes in health-related exposures, projections of health outcomes under different future emissions and adaptation scenarios, crop yields, food prices, measures of household food security, local hydrological and climate data, estimates of the vulnerability of human settlements (e.g., in urban slums or communities close to coastal areas), risk factors, and response options for extreme climatic events, vulnerability to migration as a result of sea-level changes or storms, and key health, nutrition, and demographic indicators by country and locality.

In the view of the commission the key factors to management of health effects of climate change will be: reduction of poverty and inequity in health; incentives for the development of new technologies and application of existing technologies in developing countries; change in lifestyle;

improved coordination and accountability of global governance; increase advocacy to reduce climate change trough public health awareness.

### 3.3.3. Developing diseases and Early Warning Systems

Early Warning Systems (EWS) related to infectious diseases are discussed in the World Health Organization's paper by Kuhn et al. (2005).

This WHO report presents a framework for developing disease EWS. It then reviews the degree to which individual infectious diseases are sensitive to climate variability in order to identify those diseases for which climate-informed predictions offer the greatest potential for disease control. The report highlights that many of the most important infectious diseases, and particularly those transmitted by insects, are highly sensitive to climate variations.

Subsequent sections review the current state of development of EWS for specific diseases and underline some of the most important requirements for converting them into operational decision-support systems.

Considerable research is currently being conducted to elucidate linkages between climate and epidemics. Of the 14 diseases meeting the defined criteria for potential for climate-informed EWS, few (African trypanosomiasis, leishmaniasis and yellow fever) are not associated with some sort of EWS research or development activity. For West Nile virus, an operational and effective warning system has been developed which relies solely on detection of viral activity and it remains unclear whether the addition of climatic predictors would improve the predictive accuracy or lead-time. For the remaining diseases (cholera, malaria, meningitis, dengue, Japanese encephalitis, St Louis encephalitis, Rift Valley Fever, Murray Valley encephalitis, Ross River virus and influenza), research projects have demonstrated a temporal link between climatic factors and variations in disease rates. In some of these cases the power of climatic predictors to predict epidemics has been tested.

The research reviewed in this report demonstrates that climate information can be used to improve epidemic prediction, and therefore has the potential to improve disease control. In order to make full use of this resource, however, it is necessary to carry out further operational development. The true value of climate-based early warning systems will come when they are fully integrated as one

component in well-supported systems for infectious disease surveillance and response. The report concludes that a number of steps could be taken to begin to address these issues. These include:

- Maintaining and strengthening disease surveillance systems for monitoring the incidence of epidemic diseases;
- Clarifying definitions of terminology and methods for assessing predictive accuracy;
- Testing for non-climatic influences (e.g. population immunity, migration rates and drug resistance) on disease fluctuations is dependent on the availability of appropriate data;
- Distinguishing underlying trends from interannual variability should help to avoid disease variations being attributed incorrectly to climate. More important, in practical terms, incorporating the data available for non-climatic variables should lead to greater accuracy in predictive models.

### 3.3.4. Evaluating the risks to human health related to climate change

The 2003 report entitled "Climate Change and Human Health – Risk and Responses", prepared jointly by the WHO, the World Meteorological Organization and the UNDP, provides a comprehensive update, including quantitative estimates of the total health impacts of climate change and identifies the steps necessary to further scientific investigation and to develop strategies and policies to help societies adapt to climate change.

Monitoring and surveillance systems, in many parts of the world, currently are unable to provide data on climate-sensitive diseases that are sufficiently standardized and reliable to allow comparisons over long time periods or between locations. Current research gaps include the need for more standardized surveillance of climate-sensitive health states, especially in developing countries. The assessment of climate change impacts on human health depends strongly on the availability of reliable health data to be linked with climate data, requiring measurements at local level which are often not feasible in developing countries.

Methods and tools for monitoring the effects of climate change on human health and for predicting future effects are discussed in several parts of the book.

Predicting modeling approaches are classified into several categories including:

- Statistical based models – empirical models incorporating a range of meteorological variables have been developed to describe the climatic constraints (the bioclimate envelope) for various vector-borne diseases (CLIMEX; DIMEX; GCMs);

- Process-based (mathematical) models – process-based approach is important in climate change studies as some anticipated climate conditions have never occurred before and cannot be empirically based (i.e. MIASMA);

- Landscape-based models – climate influences the habitat of pathogens and diseases vectors. There is a potential in combining climate-based models with the various environmental factors that can be measured by ground-based or remote sensing, including satellite data;

- Predictive models for early warning systems (EWS).

Exposure to climate change is estimated by predicting changes in global climate conditions for specific locations. In the current models all the population is considered as exposed. The risk of suffering health impacts also will be affected by sociodemographic conditions and other factors (e.g. environmental conditions and ecological influences) affecting vulnerability. Such variations are considered in the calculations of relative risk for each disease. The choice of the modeling approach depends on the availability of high resolution data on health states and the possibility of estimating results that comply with the framework of the overall Comparative Risk assessment.

Distinction is made between epidemiological methods and health impact assessment methods. Current epidemiological research methods are best able to deal with the health impacts of short-term (daily, weekly, monthly) variability, which require only a few years of continuous health data. In contrast, health impact assessment methods address the application of epidemiological functions to a population to estimate the burden of disease. Attributable burdens can only be estimated for those weather-disease relationships for which epidemiological studies have been conducted. The available evidence indicates that weather-disease relationships are highly context specific and vary between populations; therefore such models need to be derived from site specific data.

A detailed methodology for the quantification of the health impacts of climate change at national and local levels is provided by Campbell-Lendrum and Woodruff (2007), including the following steps: identification of climate scenarios, measurement of population exposure, quantification of the linkage between climate variables and specific health outcomes, combination of climate projections and quantitative health models, estimation of the health impacts in the absence of climate change and estimation of the climate attributable factor for each disease.

In general predictive modeling need for a multidisciplinary integrated assessment, integration between sectors, integration across the regions and the assessment of adaptation.

A broad range of data is needed to monitor climate effects on health. Where possible monitoring systems should assemble data on all components required for statistical analysis (including assessment of health modification) or process-based biological models. Relevant measurements fall into the following broad classes:

- Meteorology: various meteorological factor influence heath processes. Temperature, relative humidity, rainfall and wind speed are the most important parameters;

- Health markers: one way to address the complex causality of most health outcomes is to select indicators that are highly sensitive to climate changes, but relatively insensitive to other influences. The data requirements for attributing and measuring impacts may be quite different, depending on health issue and region. For studies of direct effects of health and cold the essential requirements is daily series of counts of death and mobility divided by age and cause, but where the intention is to look at health effects resulting from complex ecological processes, such as infectious diseases transmitted through food water or vectors, the data requirement become more complex;

- Other explanatory factors: monitoring will need to measure not just climate and health. The principal categories of modifying factors that must be considered are the following: age structure of population at risk; underlying rate of disease; level of socio economic development and existing infrastructures (water and sanitation); environmental conditions, quality of health care; specific disease control measures.

### 3.3.5. Modifiable environmental risk factors

Of specific interest is the study on modifiable environmental risk factors (Prüss-Üstün and Corválan, 2006) again published by the World Health Organization. The analysis is conducted with reference to 85 categories of diseases and is quantified in terms of “disability adjusted life years” (DAILY)s. The effects of risk factors’ reductions are evaluated in terms of reductions in diseases and related costs of the health–care system.

The definition of environmental factors includes man-made climate changes, pollution etc. and all the related behavioral and socio-economical consequences. For each environmental risk factor the

"attributable fraction" of disease is defined. The "attributable fraction" is the decline in disease or injury that would be achieved in a given population by reducing the risk (see note 1 of the previous section for a formal definition). When calculating the disease burden attributable to an environmental risk factor the analyses consider how much disease burden would decrease by reducing risk to an achievable level. The environmental fraction is a mean value and it is not necessarily applicable to an individual countries. The analysis uses data from the Comparative Risk Assessment (CRA) (WHO, 2002) and estimates for specific environmental factors not covered by the CRA.

The authors estimate that 24% of the global disease burden and 23% of all deaths can be attributed to environmental factors. Among children 0–14 years of age, the proportion of deaths attributed to the environment is as high as 36%. There are large regional differences in the environmental contribution to various disease conditions – due to differences in environmental exposures and access to health care across the regions. For example, although 25% of all deaths in developing regions are attributable to environmental causes, only 17% of deaths are attributed to such causes in developed regions. Moreover it is worth noting that this is a conservative estimate because there is as yet no evidence for many diseases. Also, in many cases, the causal pathway between environmental hazard and disease outcome is complex. Some attempts are made to capture such indirect health effects. For instance, malnutrition associated with waterborne diseases is quantified. But in other cases, disease burden is not quantifiable even though the health impacts are readily apparent. For instance, the disease burden associated with changed, damaged or depleted ecosystems in general is not quantifiable.

Diseases with the largest absolute burden attributable to modifiable environmental factors includes: diarrhea; lower respiratory infections; 'other' unintentional injuries; and malaria.

- **Diarrhea.** An estimated 94% of the diarrheal burden of disease is attributable to environment, and associated with risk factors such as unsafe drinking-water and poor sanitation and hygiene;

- **Lower respiratory infections.** These are associated with indoor air pollution related largely to household solid fuel use and possibly to second-hand tobacco smoke, as well as to outdoor air pollution. In developing countries an estimated 42% (95% confidence interval: 32 -47%) of such infections are attributable to environmental causes. In developed countries, this rate is about halved to 20% (15-25%);

- **‘Other’ unintentional injuries.** These include injuries arising from workplace hazards, radiation and industrial accidents; 44% of such injuries are attributable to environmental factors;

- **Malaria.** The proportion of malaria attributable to modifiable environmental factors is 42%, or half a million deaths annually. Policies and practices regarding land use, deforestation, water resource management, settlement siting and modified house design, e.g. improved drainage could prevent almost half of malaria incidence. The fraction amenable to environmental management, however, varies slightly depending on the region.

The large disproportions across regions and populations of the burden of diseases attributable to environmental factors give rise to ethical considerations and the need for policy measures. Public preventive health strategies are economically competitive with more traditional curative health-sector interventions. As an example, phasing out leaded gasoline can be mentioned. Indeed, estimates report that mental retardation is 30 times higher in regions where leaded gasoline is still being used. The authors recommend that policy regulations should include reducing the disease burden due to environmental risk factors as a way to eradicate extreme poverty and promote equality.

# 4. Conclusions

This paper has focused on the critical evaluation of recent quantitative assessments of health risks associated with climate change. The main contribution of our paper is to offer an integrated vision of the main scientific conclusions on the effects of climate change on human health, which are supported by the use of formal qualitative analyses.

In this respect, the journal articles surveyed in this paper have been classified according to: *i*) the statistical models adopted, which have been identified in the broad classes of time-series models, cross-section and panel analyses, equilibrium models and various other techniques; ii) the specific problems addressed, which have been referred to as primary studies, secondary studies and comparative risk assessments.

As far as more extensive reports on this subject are concerned, this specific classification has been found difficult to apply, since several contributions of this kind compare analyses of different types and methods. Therefore, we have chosen to avoid any predetermined classification, and to concentrate on the relevant findings of each outlook.

Climate change is already affecting human health, livelihoods, safety, and society and the expectation is that these effects will become greater. The climate impact is still difficult to assess with great accuracy because it results from a complex interplay of factors. It is challenging to isolate the human impact of climate change definitively from other factors such as natural variability, population growth, land use and governance. In several areas, the base of scientific evidence is still not sufficient to make definitive estimates with great precision on the human impacts of climate change. However, data and models do exist which form a robust starting point for making estimates and projections that can inform public debate, policy-making and future research. Climate change aggravates existing problems, e.g. seasonal rainfall leading to floods or water scarcity during extended droughts. Climate change acts as a multiplier of these existing risks.

For example, as the international community struggles to reduce hunger-related deaths, a warmer, less predictable climate threatens to further compromise agricultural production in the least developed countries, thereby increasing the risk of malnutrition and hunger. Think of a region suffering from water scarcity. That scarcity reduces the amount of arable land and thereby aggravates food security. The reduced crop production results in loss of income for farmers and may bring malnutrition. Health issues arise that could further diminish economic activity as family members become too weak to work.

The definition of “being seriously affected” by climate change includes someone in need of immediate assistance in the context of a weather-related disaster or whose livelihood is significantly compromised. This condition can be temporary, where people have lost their homes or been injured in weather-related disasters, or permanent, where people are living with severe water scarcity, are hungry or suffering from diseases such as diarrhea and malaria. Below we give the current best estimates of the level of impact of climate on health and likely trends in those impacts.

An estimated 325 million people are seriously affected by climate change every year. This estimate is derived by attributing a 40% proportion of the increase in the number of weather-related disasters from 1980 to current climate change and a 4% proportion of the total seriously affected by environmental degradation based on negative health outcomes.

Gradual environmental degradation due to climate change has also affected long-term water quality and quantity in some parts of the world, and triggered increases in hunger, insect-borne diseases such as malaria, other health problems such as diarrhea and respiratory illnesses. It is a contributing factor to poverty, and forces people from their homes, sometimes permanently.

Intuitively, if someone is affected by water scarcity, poverty or displacement, this also translates into health outcomes and food insecurity. Typically, climate change today mostly affects areas already seriously suffering under the above mentioned factors. Likewise, health outcomes and food insecurity lead to displacement and poverty which might result in competition for scarce resources and strains on mostly already limited government capacity to deal with deteriorating conditions and might ultimately lead to conflict. Therefore health outcomes and food security are taken as the basis for all climate change related impacts. Using this approach, the update of WHO Global Burden of Disease study shows that long term consequences of climate change affect over 235 million people today.

Global warming is expected to increasingly impact food security, water availability and quality, and exact a toll on public health, spurring chronic disease, malaria prevalence, and cardiovascular and respiratory diseases.

Current weather conditions heavily impact the health of poor people in developing nations, and climate change has a multiplying effect. A changing climate further affects the essential ingredients of maintaining good health: clean air and water, sufficient food and adequate shelter. A warmer and more variable climate leads to higher levels of some air pollutants and increases transmission of diseases through unclean water and contaminated food. It compromises agricultural production in some of the least developed countries, and it increases the hazards of weather-related disasters.

Therefore global warming, together with the changes in food and water supplies it causes, can indirectly spurs increases in such diseases as malnutrition, diarrhea, cardiovascular and respiratory diseases, and water borne and insect-transmitted diseases. This is especially worrisome because a massive number of people are already impacted by these diseases - for example upwards of 250 million malaria cases are recorded each year and over 900 million people are hungry today. Also, there is an inter-relationship among these health outcomes. For example malnutrition is linked with malaria and diarrhea which can cause significant weight loss in affected children when accompanied with food scarcity. Malaria and diarrhea can be both cause and effect of malnutrition.

Malnutrition is the biggest burden in terms of deaths. Climate change is projected to cause over 150,000 deaths annually and almost 45 million people are estimated to be malnourished because of climate change, especially due to reduced food supply and decreased income from agriculture, livestock and fisheries. Climate change-related diarrhea incidences are projected to amount to over 180 million cases annually, resulting in almost 95,000 fatalities, particularly due to sanitation issues linked to water quality and quantity. Climate change-triggered malaria outbreaks are estimated to affect over 10 million people and kill approximately 55,000. Malaria is expected to increase as an effect of increased transmission windows in some regions and because a shift in transmission to new areas is expected.

Over 90% of malaria and diarrhea deaths are borne by children aged 5 years or younger, mostly in developing countries. Other severely affected population groups include women, the elderly and people living in small islands developing states and other coastal regions, mega-cities or mountainous areas. These groups are the most affected due to social factors like gender discrimination, which can restrict women's access to health care, and age-based susceptibility as children and elderly often have weaker immune systems. Additionally, people living in certain geographic areas are more affected due factors such as high exposure to storms along coastlines, inadequate urban planning etc. Almost half the health burden occurs in the population dense Southeast Asia region with high child and adult mortality, followed by losses in Africa (23%) and the Eastern Mediterranean region. Overall, the per capita mortality rate from vector borne diseases (diseases like malaria that are transmitted by insects) is almost 300 times greater in developing nations than in developed regions (14%).

The pressure for increased precision in estimates presents a rallying cry for investment in research on the social implications of climate change. Three areas which require additional research have been identified:

- The attribution of weather-related disasters to climate change, as no consensus estimate of the global attribution has yet been made;
- Estimate of economic losses today, as the current models are forward looking;
- Regional analysis, as the understanding of the human impact at regional level is often very limited but also crucial to guide effective adaptation interventions.

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