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Climate change and malaria risk: complexity and scaling

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Abstract

The impact of climate change and other environmental changes on population health poses radical challenges to scientists. A fundamental characteristic of this topic is the pervasive combination of complexity and uncertainty. This chapter seeks to identify the nature and scope of the problem, and to explore the conceptual and methodological approaches to studying these relationships, modelling their future realization, providing estimates of health impacts, and communicating the attendant uncertainties.

Keywords: complexity; scale; modelling

Introduction

The impact of climate change and other environmental changes on population health poses radical challenges to scientists. The exploration of these systems-based risks to human health seems far removed from the tidy examples that abound in textbooks of epidemiology and public-health research (with only a few exceptions (Martens and McMichael 2002; Aron and Patz 2001)). Yet there are real and urgent questions being posed to scientists here. The wider public and its decision-makers are seeking from scientists useful estimates of the likely population health consequences of these great and unfamiliar changes in the modern world.

Clearly, there is a major task for health scientists in this topic area. This chapter seeks to identify the nature and scope of the problem, and to explore the conceptual and methodological approaches to studying these relationships, modelling their future realization, providing estimates of health impacts and communicating the attendant uncertainties.

Challenges

A fundamental characteristic of this topic area is the pervasive combination of complexity and uncertainty that confronts scientists. Policy-makers, too, must therefore adjust to working with incomplete information and with making ‘uncertainty-based’ policy decisions. Here we outline several aspects of this research domain: (i) complexity and surprises; (ii) uncertainties; and (iii) determinants of population vulnerability and adaptive capacity to these environmental changes.

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Complexity and surprises

Predicting the impact of a changing world on human health is a challenging task that requires an interdisciplinary approach drawn from the fields of evolution, biogeography, ecology and social sciences. It relies on a variety of methodologies such as integrated-assessment (IA) modelling (see below) as well as historical analysis, among other things. When even a simple change occurs in the physical environment, its effects percolate through a complex network of physical, biological and social interactions, which feed back and feed forwards. Sometimes the immediate effect of a change is different from the long-term effect; sometimes the local changes may be different from the region-wide alterations. The same environmental change may have quite different effects in different places or times. Therefore the study of the consequences of environmental change is a study of the short- and long-term dynamics of complex systems.

Uncertainties

The prediction of environmental change and its health impacts encounters uncertainties at various levels. Some of the uncertainties are of a scientific kind, referring to deficient understanding of actual processes – for example, knowing whether or not increased cloud cover arising because of global warming will have a positive or a negative feedback effect. Some of the uncertainties refer to the conceptualization and construction of mathematical models where the specification of linked processes may be uncertain or where key parameter values are uncertain. For example, what is the linkage between changes in temperature, humidity and surface water in the determination of mosquito breeding, survival and biting behaviour? Some uncertainties are essentially epistemological, referring to what we can and cannot reasonably foresee about the structure and behaviour of future societies, including for example their future patterns of emissions of greenhouse gases. And, finally, there is of course the familiar source of uncertainty that arises from sampling variation, and which leads to the need for confidence intervals around point estimates.

Vulnerability and adaptation

Human populations vary in their vulnerability to health hazards. A population's vulnerability is a function of the extent to which a health outcome is sensitive to climate change and of the capacity of the population to adapt to new climate conditions. The vulnerability of a population depends on factors such as population density, level of economic development, food availability, local environmental conditions, pre-existing health status, and the quality and availability of public health care.

Adaptation refers to actions taken to lessen the impact of the (anticipated) climate change. There is a hierarchy of control strategies that can help to protect population health. These strategies are categorized as: (i) administrative or legislative; (ii) engineering, or (iii) personal (behavioural). Legislative or regulatory action can be taken by government, requiring compliance by all, or by designated classes of persons. Alternatively, an adaptive action may be encouraged on a voluntary basis, via advocacy, education or economic incentives. The former type of action would normally be taken at a supranational, national or community level; the latter would range from supranational to individual levels. Adaptation strategies will be either reactive, in response to observed climate impacts, or anticipatory, in order to reduce vulnerability to such impacts.

Modelling the impact of climate change on malaria

Models incorporating a range of meteorological variables have been developed to describe a specific 'bioclimate envelope' for malaria. Multivariate statistical techniques can be used to select predictive variables (whether meteorological or environmental, ground-based or remotely-sensed). Models that match the presence of a particular species with a discrete range of temperature and precipitation parameters can be used to project the effect of climate change on vector redistribution.

Some mosquito species have been successfully mapped in Africa using meteorological data (Lindsay, Parson and Thomas 1998). Meteorology is usually recorded at ground level, but coverage can be relatively sparse or inappropriate, especially in developing countries (Hay et al. 1996). Grid surfaces interpolated from these data often form the basis for modelling the relationship between vectors/disease and climate, though averaging and interpolation to large grid boxes leads to (as yet unresolved) methodological problems of scaling when making inferences to point estimates (Patz et al. 2002; Hay et al. 2002). Remotely-sensed imagery from space satellites is often used as surrogate for instrumental meteorological data and has the advantages of wide coverage, fine resolution, consistency and providing a synoptic view. In addition, compound indices may be useful: the Normalized Difference Vegetation Index (NDVI), based upon the difference ratio of reflected red and near-infrared energy, correlates well with photosynthetic activity of plants, rainfall and saturation deficit and has also been correlated with the distribution of vectors and disease (Hay et al. 1996).

Rogers has mapped the changes of three important disease vectors (ticks, tsetse flies and mosquitoes) in Southern Africa under three climate-change scenarios (Hulme 1996). The results indicate significant changes in areas suitable for each vector species, with a net increase for malaria mosquitoes (*Anopheles gambiae*). The final objective of such work is to map human disease risk but the relationship between vector-borne disease incidence and climate variables is complicated by many socio-economic and environmental factors.

Another example of an empirical statistical model is the CLIMEX model. This model, developed by Sutherst, Maywald and Skarratt (1995), maps the translocation of species between different areas as they respond to climate change. The assessment was based on an 'ecoclimatic index', governed largely by the temperature and moisture requirements of the malaria mosquito. CLIMEX analyses conducted in Australia indicate that the indigenous vector of malaria would be able expand its range 330 km south under one typical scenario of climate change. However, these studies clearly cannot include all factors that affect species distributions. For example, local geographical barriers and interaction/competition between species are important factors that determine whether species colonize the full extent of suitable habitat (Davis et al. 1998). Assessments may also include additional dynamic population (process-based) models (Sutherst 1998).

Martin and Lefebvre (1995), using a similar approach, developed a Malaria-Potential-Occurrence-Zone (MOZ) model. This model was combined with 5 GCMs (General Circulation Models) to estimate the changes in malaria risk based on moisture and minimum and maximum temperatures required for parasite development. This model corresponded fairly well with the distribution of malaria in the 19th century and the 1990s, after allowing for areas where malaria had been eradicated. An important conclusion of this modelling exercise was that all simulation

runs showed an increase in seasonal (unstable) malaria transmission, under climate change, at the expense of perennial (stable) transmission.

Rogers and Randolph (2000), using a multivariate empirical-statistical model, found that, for the IS92a (business as usual) climate-change scenario, there is no significant net change by 2050 in the estimated portion of the world population living in malaria-transmission zones: malaria increased in some areas and decreased in others. The outcome variable in this model is based on present-day distribution limits of malaria. However, using current distribution limits in the estimate may have yielded a biased estimation of the multivariate relationship between climatic variables and malaria occurrence, since the lower temperature range in temperate zones (especially Europe and southern USA), would have been treated as climatically unsuitable for malaria. However, it may be that these portions of multivariate climate space were captured in the model because malaria persists in climatically similar regions (e.g. parts of Asia). These hypotheses are currently being tested by sensitivity modelling (Thomas in prep.).

An integrated, process-based model to estimate climate-change impacts on malaria (that is part of the MIASMA modelling framework), has been developed by Martens and colleagues (Martens 1995b; 1995a; 1999). This model differs from the others in that it takes a broad approach in linking GCM-based climate-change scenarios with a module that uses the formula for the basic reproduction rate (R_0) to calculate the 'transmission or epidemic potential' of a malaria-mosquito population. The use of the basic reproduction rate is defined as the number of new cases of a disease that will arise from one current case when introduced into a non-immune host population during a single transmission cycle (Anderson and May 1991). This goes back to classical epidemiological models of infectious disease. Model variables within R_0 that are sensitive to temperature include: mosquito density, feeding frequency, survival, and extrinsic incubation period. The extrinsic incubation period (i.e., the development of the parasite in the mosquito) is particularly important. The minimum temperature for parasite development is the limiting factor for malaria transmission in many areas.

Tol and Dowlatabadi (2001) integrated the results of MIASMA within the FUND framework, developed by Tol, to estimate the trade-off between climate change and economic growth on malaria risk. The first results of this exercise show the importance of economic variables in estimating changes in future malaria risk. Although this exercise indicates the importance of including the economic dimension in analysing climate-change impacts upon future malaria risk, their approach may be too simplistic (Martens and McMichael 2001).

Gallup and Sachs (2001) explored the correlation between the malaria index and income levels. They took into account some of the factors that also affect malaria risk (e.g. low agricultural productivity, presence of other tropical diseases, colonial history and geographical isolation). The malaria index is defined as the fraction of the population living in areas of high malaria risk in 1994, times the fraction of malaria cases in 1990 that are of the malignant *Plasmodium falciparum* species. The malaria index showed a strong negative association with income levels, indicating that income grows more slowly in countries where the disease is present. This trend appears to apply equally to countries in Africa and in other continents. In countries that include large malaria-free regions (e.g. Brazil, Venezuela, Malaysia, Indonesia, Turkey, Kenya and Ethiopia), the prevalence of infection correlates with poverty. Malaria, of course, is not the sole determinant of poverty, just as poverty alone does not explain the distribution of malaria.

All of the examples discussed above have their specific disadvantages and advantages. For example, the model developed by Rogers and Randolph (2000) incorporates information about the current social, economic and technological modulation of malaria transmission. It assumes that those contextual factors will apply in future in unchanged fashion. This adds an important, though speculative, element of multivariate realism to the modelling – but the model thereby addresses a qualitatively different question from the biological model. The biological model of e.g. Martens and colleagues (1998; 1999) assumes that there are known and generalizable biologically mediated relationships. Also, this modelling is only making a start to include the horizontal integration of social, economic and technical change. The statistical model is based on socio-economically censored data. It derives its basic equation from the existing (constrained) distribution of malaria in today's world and climatic conditions, and foregoes much information on the malaria–climate relationship within the temperate-zone climatic range. Yet this range is likely to be considerably important in relation to the marginal spread of malaria under future climate change.

Characterizing the relationship between socio-economic development and malaria incidence is difficult for various reasons: First and foremost, malaria incidence is hugely influenced by geography and prevailing climate. Hence, since the world's poorest countries tend to be in high-risk tropical and subtropical regions, it is inevitable that national rates of malaria incidence correlate with per capita income. Apportioning malaria causality between environment, income and social practices is, therefore, problematic. Other related reasons include: i) The income per capita at a country or regional level is an inadequate description of how that wealth is distributed within a society and to what public uses it is applied (e.g. Costa Rica and Cuba, with lower per capita income, outperform Brazil in social and health indices); ii) Political instability can undermine the influence of development (i.e. Russia, Azerbaijan); iii) Economic development can increase transmission temporarily (e.g. deforestation, population movement, water development projects); iv) Many control programmes depend on external/donor funding (e.g. Viet Nam) from richer, developed countries.

Furthermore, the quality of malaria data is very poor in most developing countries. National indicators of malaria include national mortality or morbidity data. Mortality data generally reflect *P. falciparum* transmission as *P. vivax* is rarely fatal. Further, in areas with very high levels of transmission where nearly everyone is infected, with or without immunity, the morbidity figures are meaningless. Estimates can vary considerably from year to year because of changes in reporting rather than a true change in disease transmission. For these reasons therefore, a straightforward relationship between national income per capita and malaria status is not very likely.

Little research has been carried out on the determinants of vulnerability of populations to malaria, so it is difficult to develop assumptions about future adaptation to changes in disease risk associated with climate change and economic development. Populations can respond to changes in local malaria transmission associated with climate change. With planning and development of adaptation capacity, potential increases in disease incidence associated with climate change may be largely prevented. However, the effectiveness of adaptation responses will vary depending on the circumstances of the population at risk.

In tropical countries, successful prevention and control in the future would probably involve *technical*, *political* and *socio-economic adaptation*. Technical adaptation includes for example the use of insecticides. Political adaptation involves adequate administration of control programmes, funding of research and training,

investments in health infrastructure etc. It should be noted here that, after the initial success of global eradication programmes of the 1950s and 1960s, resources available from international agencies have declined along with those of national governments. The disease is now resurgent in many countries where it previously had been controlled. However, the relation between the level of malaria incidence and political willingness to adapt policy is unknown. In the meantime, it is not clear to what extent economic growth on its own will reduce the incidence of malaria.

A matter of scale

The problem of modelling the impacts of global (environmental) change processes on human health is that it has to cope with a variety of processes that operate on different temporal and spatial levels and differ in complexity.

First, modelling has to connect disciplinary processes that differ by nature: physical processes, monetary processes, social processes and policy processes. Because of the multitude of disciplinary processes to be combined, a representation as simple as possible of disciplinary knowledge is preferable. There is, however, no unifying theory how to do this. In addition, the processes to be linked are usually studied in isolation from each other. This isolation is needed as part and parcel of the classic model of scientific progress and discovery. However, when the constraints of isolation are removed, there is a variety of ways in which to connect the reduced pieces of disciplinary knowledge. This manifold of possible integration routes, for which there is no unifying theory, is one of the reasons why quality control is so difficult to achieve in IA modelling. For instance, in order to link the reduced pieces of disciplinary knowledge in a systemic way, one can use elements from classical systems analysis, or the method of system dynamics, or a sequential input–output analysis, or a correlation-based approach, or a pressure–state–impact–response approach.

Second, modelling has to deal with different spatial scale levels. One of the ultimate challenges in modelling is to connect higher scale assessments with lower scale ones. So far, there has been hardly any experience with playing around with scale levels in modelling. Down-scaling or up-scaling the spatial level of a model has profound consequences. This is related to the question to what extent the processes considered are generic or spatially bound in character. In other words: does a relationship at one scale hold at larger or lower scale levels?

Third, modelling is faced with a multitude of temporal scales. Short-term needs and interests of stakeholders have to be considered. However, biogeochemical processes usually operate on a long time scale, whereas economic processes operate on short to medium time scales. Another challenging aspect of modelling is to interconnect long-term targets as specified as a result of analysing processes operating on longer-term time scales, with short-term goals for concrete policy actions. Unfortunately, there is not yet a sound scientific method how to do this, thus far only heuristic methods have been used.

In Figure 1, for example, some important factors determining malaria risk are depicted along ‘temporal’ and ‘spatial’ scale axes. Looking at the climate, human and mosquito system, it is apparent that they vary in their spatial and temporal scale: mosquito larval development takes place at the level of puddles and at time scales varying from days to weeks, climate change is a process influencing the global climate system at time frames of years to centuries or more, whereas economic

processes operate on short to medium time scales. Furthermore, short-term needs and interests of stakeholders have to be considered.

Although the assessment of malaria risk may be done on a variety of geographical scales – varying from a village to an entire country, region or the world as a whole – so far there has been no formal analysis of the effect of scaling on models or our understanding. Varying geographical (extent) and measurement (resolution) scales has profound implications for spatial analysis. This is formalized as the Modifiable Areal Unit Problem (MAUP) (Openshaw 1984), and is fundamental to the analysis of geographical data (Flowerdew, Geddes and Green 2001). MAUP has become an important but overlooked issue for our understanding of malaria as many studies are now geographically based. An equally important issue, already alluded to, is scaling mismatches when interpreting events at one scale against data measured at another. In the pilot analysis presented below we explore these differences in spatial scale (the same effects will be evident in mismatched temporal series).

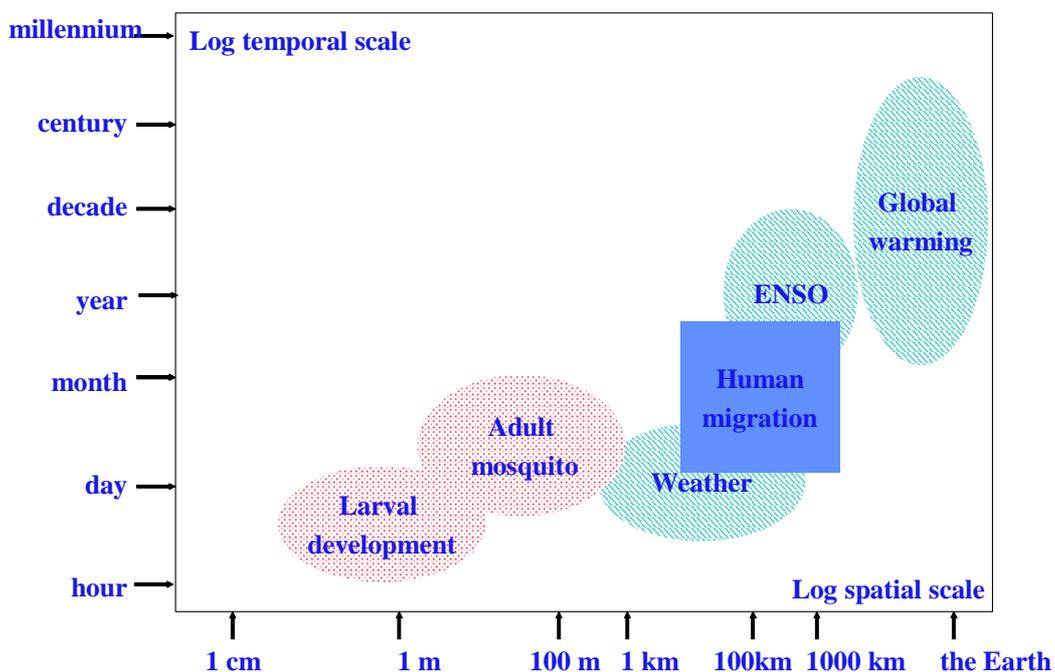


Figure 1. Some processes on different temporal and spatial scales that affect malaria epidemiology

In seeking spatial structure it is instructive to compare the variation in measurements among locations at increasing distances, in the likelihood that locations closer together will be more similar than locations further apart. Here we employed an exploratory geostatistical approach by calculating the semivariance (Oliver 2001) (as variance among locations increases, the semivariance also increases) in four measurements relevant to malaria in Africa. The first two are estimates of the climatic suitability for *falciparum* malaria transmission based upon 0.5-degree grid cell length surfaces of 1961-90 observed mean climate (<http://ipcc-ddc.cru.uea.ac.uk>) using the MARA/ARMA spatial fuzzy-logic model (Craig, Snow and Le Sueur 1999): i) spatial extent (Figure 2, see Colour pages elsewhere in this book) – the suitability for malaria transmission in four consecutive months (fuzzy values from 0 to 1); ii) seasonal extent (Figure 3, see Colour pages elsewhere in this book) – number of consecutive months suitable for transmission (fuzzy values from 0 to 12). We used this index as a proxy

from climate, rather than a single measure such as temperature because it incorporates both temperature and precipitation thresholds for disease transmission.

The second two measurements are entomological values (biting rate and entomological inoculation rate, EIR) recorded in the field at specific locations across Africa (Figure 4) and compiled by Hay et al. (2000).

Our analyses were designed to indicate general differences in spatial structure and are not exhaustive (a variety of lags and bounding regions could have been tried) or complete (for instance there are methodological inconsistencies in the entomological measurements, see Hay et al. (2000)).



Figure 4. Locations where EIR and (for a sub-set) biting rate have been recorded (derived from Hay et al. (2000))

Climate-based estimates of malaria distribution and seasonality showed long-range variation, with a sill variance (asymptote) at around 30 degrees separation. As might be expected from interpolated values, variance increased smoothly with increasing separation (Figure 5 a,b). In contrast, semivariograms of location-specific biting rates and EIR showed no obvious spatial structure, with measurements varying randomly over space (Figure 5 c,d) at least for lags of 0.5 degrees.

The lack of spatial structure in biting rate and EIR will likely be due to sampling errors and inconsistencies and, more importantly, local variation in environment not captured at 0.5-degree lags. In other words, to compare biting rate and EIR usefully with climate it would be necessary either to aggregate entomology measures to climate grid boxes or to use meteorological data local to the entomological studies. For the former, we urgently need to know the spatial structure (if any) of malaria entomological and clinical measurements, and how this varies among regions, so that we can determine optimal aggregation scales and hence relate them to other aggregated variables such as climate. For the latter, we need more consistent long-term measurements tied to local meteorological stations. Initiatives such as the INDEPTH network (see chapter by Sankoh and Binka in this volume) are an essential step forward for both solutions.

Geographical scaling is not the only important issue. For instance, an early version of the malaria model developed by Martens et al. (1995) uses a composite measure of different species of *Anopheles*. This globally aggregated model assumed that there are universal relationships that are sufficiently dominant to ensure a valid approximate

overall forecast. Later versions of the model (Martens et al. 1999) include species-specific relationships (as far as available in literature) between climate and transmission dynamics. Even so, the equations within a global model may well be inappropriate for particular local conditions. This example of hierarchical (in this case, taxonomic) scaling demonstrates another area where informed decisions need to be made in modelling.

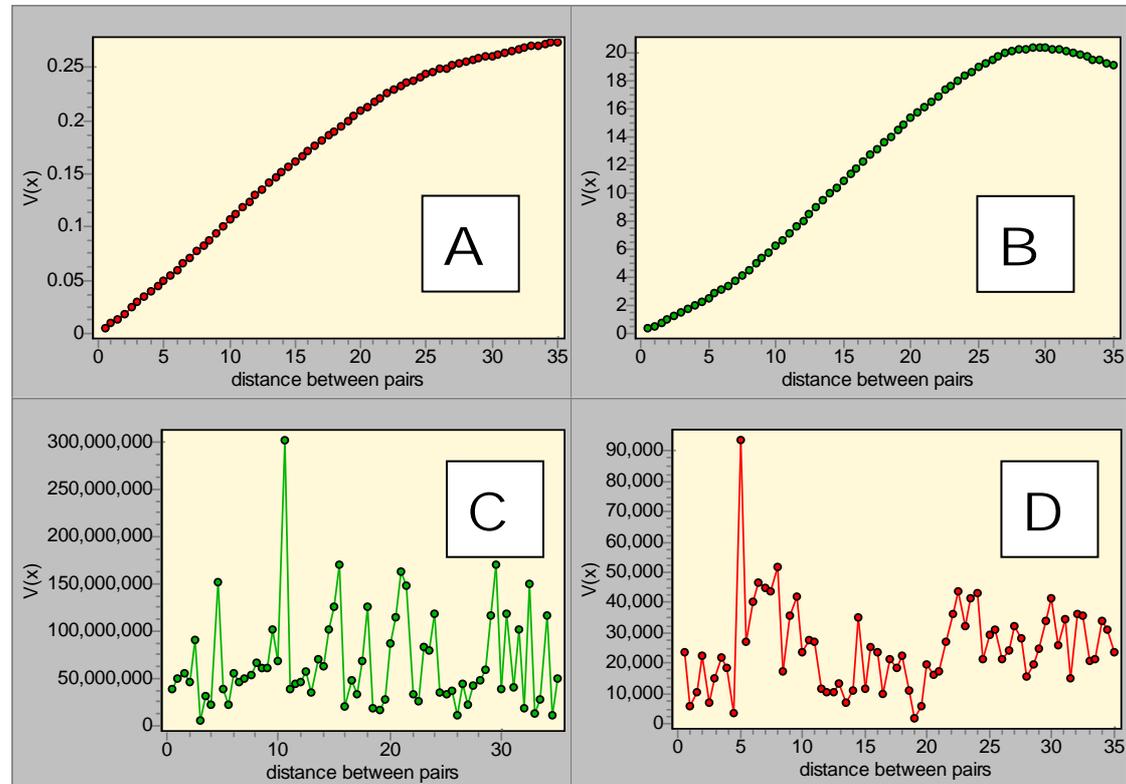


Figure 5. Omnidirectional semivariograms (moments estimator) with lag of 0.5 degrees, over 0.5-35 degrees extent. A) MARA/ARMA index of climatic suitability for *P. falciparum* transmission in four consecutive months; B) Number of consecutive months with a MARA/ARMA index of climatic suitability for *P. falciparum* transmission of $p \geq 0.9$ in each month; C) biting rate; D) entomological inoculation rate

In this context, an interesting approach is proposed by Root and Schneider (1995): the so-called Strategic Cyclical Scaling (SCS) method. This method involves continuous cycling between large- and small-scale assessments. Such an iterative scaling procedure implies that a specific global model is disaggregated and adjusted for a specific region or country. The new insights are then used to improve the global version, after which implementation for another region or country follows. In malaria modelling some progress has been made (Lindsay and Martens 1998). This SCS method can also be used for conceptual validation of models.

The trend in current modelling is to move toward greater and greater disaggregation, assuming that this yields better models (Rotmans and Van Asselt 2000). In general, it is difficult to know when to stop building more detail into an IA model. Past decades of model building have shown that small and transparent models are often superior in that they provide similar results to large models faster and offer ease of use. In this respect, it is useful to distinguish between *complicated* and *complex* models. Complicated models are models that include a variety of processes,

many of which may be interlinked. If incremental changes in these processes generally lead to incremental changes in model output, one can conclude that the dynamics of the model are almost linear and not complex at all. The more complicated the model, the higher the possibility of errors and bugs. It requires thorough testing to pick up most if not all errors and bugs, an activity which is, unfortunately, heavily underrated. Complex models, however, contain relatively few processes, but incremental changes in these processes may result in considerable changes in the results of the overall model. This non-linear behaviour, due to the inclusion of feedbacks, adaptation, self-learning and chaotic behaviour, is often unpredictable.

Practically speaking, this means that disaggregation of models has profound consequences for the dynamics of the model. Breaking down a global model into various regions requires that the regional dynamics be dealt with in an adequate manner. Current regional models use grid cells or classes for representing geographical differences and heterogeneities in regional models. They do not capture, however, the regional dynamics with regard to population growth and health, economic development, resource use and environmental degradation, let alone regional interactions through migration and trade.

The way ahead

As the *full* complexity of the interactions between global developments and human health cannot be satisfactorily reduced to modelling, what is the role of such modelling? Despite the difficulties and limitations of the modelling process, models first of all draw attention to the potential health impact of these global changes. Second, they may indicate the relative importance of the factors that influence these outcomes. This enhances public discussion, education and policy-making. However, even more important is the role modelling plays in the systematic linkage of multiple cause-and-effect relationships based on available knowledge and reasoned guesses. This should increase our understanding of the health impacts of global changes, and identify key gaps in data and knowledge needed to improve the analysis of these effects.

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