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T8.2: Population at malaria risk in Africa: 2005, 2015 and 2030

**Dr Simon I. Hay
Dr Andrew J. Tatem
Dr Carlos A. Guerra
Professor Robert W. Snow**

**Centre for Geographic Medicine
KEMRI /Wellcome Trust Collaborative Programme, Kenya
University of Oxford, UK**

Abstract:

We have simulated the combined effects of climate change, population growth and urbanisation on the population at risk (PAR) of *Plasmodium falciparum* malaria in Africa. PAR is defined as the number of people living in areas of climatic suitability for stable *P. falciparum* malaria transmission. The results suggest that the PAR will change from approximately 0.63 billion in 2005, to 0.87 billion in 2015 and 1.15 billion in 2030. These PAR numbers are presented sequentially for each of these influences, so that the magnitude of each effect and its direction could be established before they were integrated.

The majority of this future PAR change can be attributed to the massive rates of population growth expected on the continent. These PAR changes are reduced slightly because populations in large urban areas suffer reduced malaria risk. Climate change is likely to further increase the numbers at risk. These increases were small, however, when compared with demographic changes. There also remain considerable difficulties in disentangling the effects of real climate change from artefacts introduced by comparing our detailed spatial knowledge of climate today with the poor spatial resolution models of the future. These results are discussed against a background of existing work and a previous review (Snow et al., 2006) that outlined the suite of additional drivers that will affect the evolution of malaria's epidemiology in the next quarter of a century.

Some of the difficulties in using PAR to estimate future morbidity and mortality rates are also discussed. Research avenues are suggested to improve this work by: (i) understanding better assumptions made in demographic change; (ii) incorporating additional land-use change influences; and, (iii), most importantly, moving to a probabilistic treatment of uncertainty so that the true confidence of such estimates can be conveyed unambiguously to policymakers.

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Contents

Population at malaria risk in Africa: 2005, 2015 and& 2030	1
Contents.....	1
1. SUMMARY FOR POLICYMAKERS	3
2. TECHNICAL SUMMARY.....	6
3. INTRODUCTION.....	7
4. CLIMATE CHANGE IMPACTS ON MALARIA.....	8
4.1. Climate change impacts review.....	8
4.2. Climate change impact methods	12
4.3. Climate change impacts results	14
4.4. Climate change impacts discussion.....	15
5. POPULATION GROWTH IMPACTS ON MALARIA	16
5.1. Population growth impacts review	16
5.2. Population growth impacts method.....	17
5.3. Population growth impacts results and discussion.....	18
6. URBANIZATION IMPACTS ON MALARIA.....	19
6.1. Urbanization impacts review.....	19
6.2. Urbanization impacts methods	21
6.3. Urbanization impacts results and discussion.....	21
7. INTEGRATED IMPACTS	21
7.1. Integrated impacts review	21
7.2. Integrated impacts methods.....	22
7.3. Integrated impacts results.....	22
7.4. Integrated impacts discussion.....	23
8. FUTURE RESEARCH PRIORITIES	24
9. ACKNOWLEDGEMENTS	25
10. GLOSSARY	26
11. REFERENCES.....	27
Appendix 1: Explaining location and spatial resolution	45
Appendix 2: The FCS index for stable <i>P. falciparum</i> malaria transmission.....	46
Appendix 3: The UNPD-WPP global human population projections.....	47
Appendix 4: Defining urban and rural populations at the continental scale	48
Appendix 5: A rubric for correcting FCS for urbanization.....	50

1. SUMMARY FOR POLICYMAKERS

Method. Malaria risk in Africa can be described using a climate-based model for the stability of *Plasmodium falciparum* malaria transmission. Alternative ways to achieve this definition of risk have been used by others and are reviewed. Overlaying these risk maps on population surfaces enables the population at risk (PAR) of malaria to be determined. In this way the same malaria risk model is used to provide the most widely accepted estimates for malaria burden (annual morbidity and mortality totals) for the African continent.

Since the malaria risk model is based on temperature and rainfall, future movements in these factors described by climate change models can be used to generate the same climate-based risk maps for the future. Differences between those maps and the contemporary situation give insight into how the future climate may favour or hinder malaria transmission. For the purposes of this exercise we look for changes from 2005 shown by years 2015 and 2030. Detailed maps on the distribution of human population are also available. To these may be applied forecasted population growth rates to derive maps of future human population distribution. Future demographic changes can, therefore, be easily integrated.

The malaria risk model uses only climate, so additional insight into fine resolution risk modifiers such as land-use changes are not incorporated. One of the most important of these is the reduction in malaria risk caused by urbanization in Africa. This occurs because urban conditions make life less suitable for the mosquito vector (offering, for example, less abundant and more polluted breeding sites) and better for humans (for example, improved socioeconomic status and physical access to preventive and curative measures). The urban and rural status of a population can be inferred from the population density at which people live. Previous work has shown how we need to reduce

risk attributed to urban populations. Therefore, a combination of climate-based malaria risk models, human population maps and projections of how these will change can be used to simulate the relative impacts of climate change, population growth and urbanization of the future of malaria in Africa in the next 25 years.

Considering these influences independently enables us to appreciate the extent and direction of each impact before they were collated to provide an integrated assessment. It is emphasised that the influence of many other drivers, such as other land-use changes, socioeconomics and the HIV/AIDS epidemic were not considered, so that the results of these simulations must be considered preliminary.

Results. The climate change impacts were investigated first. The most widely used climate change models predict future climate at a coarse 450 x 300 km spatial resolution. Climate surfaces for today exist at 20 x 20 km spatial resolution. There were unexpected difficulties in comparing these data, because we could not differentiate true climate change from artefacts that may have been introduced by interpolation to a common resolution. We emphasise these concerns, generic to all such impact evaluations, through a series of case studies. After highlighting these difficulties, we focus, for the purposes of this report, on the results of using a contemporary climate and a future interpolated climate prediction to its spatial resolution, as this most closely parallels previous work. This found PAR increased from 0.638 to 0.722 (+13.075% of baseline) and 0.731 billion (+14.495% of baseline) by 2015 and 2030 respectively.

Demographic changes in the absence of climate change were then explored. PAR increased from the 0.638 to 0.781 (+22.426% of baseline) and 1.031 billion (+61.485% of baseline) by 2015 and 2030 respectively. These changes were due to population growth alone. When applying the reduced risk due to urbanization the increases were still dramatic from 0.627 to 0.758

(+20.876% of baseline) and 0.972 billion (+54.994% of baseline) by 2015 and 2030 respectively. Finally, integrating these climate change, population growth and urbanization impacts showed PAR increased from 0.626 to 0.865 (+38.006% of baseline) and 1.146 billion (+82.922% of baseline) by 2015 and 2030 respectively.

Conclusions. We emphasise most strongly that the level of uncertainty in the PAR numbers is not quantified and that this should be paramount in any use and discussion of these numbers. Due to the sheer magnitude of the demographic influences, we can state with relative confidence, however, that the majority of this change in population at risk will be due to the inexorable progression of population growth. The results further show that this will be exacerbated by climate change and modulated by the effects of urbanization. International targets on malaria control, therefore, will face a considerable challenge even to maintain the *status quo*. We have not considered the myriad of other drivers of malaria outlined in a previous review, so these findings must also be considered preliminary.

Improving the accuracy of these PAR estimates and providing estimates of their fidelity is necessary to provide a more reliable evidence base for policymakers. Specific research avenues are suggested to improve this work by (i) understanding better assumptions made in demographic change (ii) incorporating additional land-use change influences, and (iii), most importantly, moving to a probabilistic treatment of uncertainty so that the true confidence of such estimates can be conveyed unambiguously to policymakers. Due to the magnitude of its effects on the PAR of malaria and its cross-sectoral impact, demographic changes should be as high on our research and policy agenda in the next 25 years as climate change.

2. TECHNICAL SUMMARY

We have simulated the combined effects of climate change, population growth and urbanisation on the population at risk (PAR) of *Plasmodium falciparum* malaria in Africa. PAR is defined as the number of people living in areas of climatic suitability for stable *P. falciparum* malaria transmission. The results suggest that the PAR will change from approximately 0.63 billion in 2005, to 0.87 billion in 2015 and 1.15 billion in 2030. These PAR numbers are presented sequentially for each of these influences, so that the magnitude of each effect and its direction could be established before they were integrated.

The majority of this future PAR change can be attributed to the massive rates of population growth expected on the continent. These PAR changes are reduced slightly because populations in large urban areas suffer reduced malaria risk. Climate change is likely to further increase the numbers at risk. These increases were small, however, when compared with demographic changes. There also remain considerable difficulties in disentangling the effects of real climate change from artefacts introduced by comparing our detailed spatial knowledge of climate today with the poor spatial resolution models of the future. These results are discussed against a background of existing work and a previous review (Snow *et al.*, 2006) that outlined the suite of additional drivers that will affect the evolution of malaria's epidemiology in the next quarter of a century.

Some of the difficulties in using PAR to estimate future morbidity and mortality rates are also discussed. Research avenues are suggested to improve this work by: (i) understanding better assumptions made in demographic change; (ii) incorporating additional land-use change influences; and, (iii), most importantly, moving to a probabilistic treatment of uncertainty so that the true confidence of such estimates can be conveyed unambiguously to policymakers.

3. INTRODUCTION

Scenarios analysis (SA) is an exploration of possible futures, based on hypothetical storylines, with the objective of improving decision-making by providing a comprehensive appraisal of various outcomes and their implications. Most SA studies have aimed to be global and thematically comprehensive and to project changes through to the year 2100 (Gallopín *et al.*, 1997; Hammond, 1998; Raskin *et al.*, 1998; Raskin *et al.*, 2002; U.N.E.P., 2002). They have thus sacrificed the possibility of quantitative analyses. Their results and recommendations, therefore, tend to be general and their policy advice necessarily diffuse. Furthermore, in a recent review of the health components of a suite of global SAs, health developments were often found to be poorly described and non-systematically treated (Martens and Huynen, 2003).

Here we have the relative luxury of considering only *P. falciparum* malaria in Africa and only until 2030. In order to consider these changes quantitatively, we deal only with information for which there is explicit spatial detail at continental scale. Currently, of those drivers known to influence populations at risk of malaria (Snow *et al.*, 2006) these are climate change, demography and urbanization. Research directions for investigating other land-use change phenomena, such as changes in forest, agriculture, irrigation, dams and desert extents are also outlined. Other potential impacts such as the HIV/AIDS epidemic, interventions, nutrition, poly-parasitism and socio-economic changes have been discussed qualitatively (Snow *et al.*, 2006) and are not considered further.

Note that this document uses terms widely deployed in meteorology and epidemiology that may not be familiar to all readers. The more commonly-used and important of these are defined in the glossary. Similarly, there is the frequent quoting of spatial resolution in units derived from the latitude and longitude reference system. This is so common in the relevant literature that it

would be churlish to change, so Appendix 1 gives a brief digest of how these units are derived and a table of their approximate conversion into kilometres. Technical details are kept to the appendices, except where they are crucial for understanding and/or are novel for this iteration of the work.

4. CLIMATE CHANGE IMPACTS ON MALARIA

4.1. Climate change impacts review

Many authors have used different techniques to investigate the impact of climate change on malaria at the national (Hartman *et al.*, 2002), continental (Tanser *et al.*, 2003; Thomas *et al.*, 2004) and global level (Martin and Lefebvre, 1995; Matsuoka and Kai, 1995; Martens *et al.*, 1999; Rogers and Randolph, 2000; van Lieshout *et al.*, 2004). To date, there has been little consensus on interpreting and reporting results, which makes them difficult to compare. The main conceptual approaches and results are outlined below.

The modelling approaches can be divided into the statistical and the biological. The statistical exercises simply pattern-match contemporary climate measurements to the current malaria range and then apply these same numerical relationships to possible future climates to predict the future malaria distribution. A widely-cited example of the statistical approach (Rogers and Randolph, 2000) uses maximum likelihood techniques to establish the current multivariate climatic constraints to the 2002 distribution limits of malaria globally (*P. falciparum* and *P. vivax*), using a 1961-1990 0.5° x 0.5° climatology (New *et al.*, 1999; New *et al.*, 2000) for the baseline and this surface plus interpolated HadCM2 difference fields (Hulme *et al.*, 1999) [http://ipcc-ddc.cru.uea.ac.uk/sres/hadcm2_download.html] for the future. These results, when applied to future climate projections, predict future malaria distributions that show remarkably few changes relative to the existing distribution limits, even under the most extreme scenarios. Global results under the HadCM2 A2

scenario, for example, found an additional 23 million people at risk under the medium-high variant by 2050 (0.84% of baseline) and -25 million under the high variant (-0.92% of baseline). Note that population growth was not incorporated, so these PAR changes are all calculated with reference to a constant 1995 population surface.

Rogers and Randolph (2000) have been criticised for using the contemporary rather than historical malaria distribution, with the suggestion that this biased it towards establishing multivariate relationships relatively inert to future climate change, as they were sampled from the centre of ancestral malaria distribution (McMichael *et al.*, 2001a). This is being tested with the recorded changing global distribution of malaria (Hay *et al.*, 2004b) and new information on the distribution limits of *P. falciparum* and *P. vivax* in 2005 (Guerra *et al.*, 2006).

These statistical approaches can also be criticised because they assume that the relationships between climate and malaria will remain unchanged into the future. Biological or process-based models can potentially overcome this limitation, as they attempt to capture more intelligently the effect of climate on disease transmission processes.

A series of “biological” models have used a rearranged form of the basic reproduction equation (R_o) for malaria to define a transmission potential (TP, the reciprocal of the critical mosquito density required to sustain malaria transmission), coupled to climatologies and climate model simulations of the future, in order to predict impacts (Martens *et al.*, 1999). The R_o was first introduced into epidemiology in relation to malaria by MacDonald (Macdonald, 1952) and is usually defined as the secondary number of cases that result from the index case in a totally susceptible population *i.e.* an epidemic process. Thus, if $R_o < 1$ the possibility is for only minor epidemic outbreaks and the disease does not persist. If $R_o > 1$ there is a positive chance of an epidemic and persistence. If $R_o \gg 1$ this chance is greater (Dietz, 1993).

While the philosophy of the approach is appropriate, the reality as implemented (Martens *et al.*, 1999; van Lieshout *et al.*, 2004) has been criticised (Rogers and Randolph, 2000; Rogers and Randolph, 2006). One of the most significant criticisms of the TP model is that, because several variables on which the effects of climate change could not be quantified (such as the transmission coefficient from vertebrate to vector and from vector to vertebrate, as well as, the rate of recovery of the host from infection), they were set to one in the equations. This allows irregularities such as the possibility for increased transmission potential in areas where R_0 is less than one (Rogers and Randolph, 2000; Rogers and Randolph, 2006).

This TP model has been further ‘refined’ in the most recent predictions (van Lieshout *et al.*, 2004) by defining PAR only in locations where TP indicates suitability for transmission for more than three months of the year and annual total rainfall exceeds 80mm. The fact that these additions are necessary to more closely describe reality underscores how the research community is currently unable to implement a comprehensive biological model for malaria transmission to which meteorological variables can be coupled. We have ignored in this review previous iterations of the same model that do not include these stricter suitability criteria (Martens *et al.*, 1995; Martens, 1995; Martens *et al.*, 1997; Martens, 1998). It is important to emphasize that all these papers are evolutionary steps of identical models and not independent studies, as has been implied in the Intergovernmental Panel on Climate Change summary for policy makers (I.P.C.C., 2001; McMichael *et al.*, 2001b) which leads the reader to the erroneous conclusion that these studies represent a balance of evidence. Using these more stringent criteria on a 1961-1990 $0.5^\circ \times 0.5^\circ$ baseline climatology (New *et al.*, 1999; New *et al.*, 2000) and the interpolated HadCM3 A2 scenario, the results show an increase in risk in sub-Saharan Africa of approximately 53 million persons by 2080 (van Lieshout *et al.*, 2004). The paper acknowledges that this is probably an overestimate, as no attempt is made to discount for the

decrease in malaria risk in urban areas, which has been shown to be important (Robert *et al.*, 2003; Hay *et al.*, 2005a). It is also impossible to determine the relative contribution of climate change and population growth from the way that the results are presented in this report. Globally, this scenario predicts a net decrease of 141 million PAR, although this can range from +100 to -153 million people between the scenarios and their variants.

To model the impacts of climate change on malaria risk in Africa, a hybrid, statistical-biological model approach has also been adopted (Thomas *et al.*, 2004) using the FCS as outlined by (Craig *et al.*, 1999). See Appendix 2 for a detailed description of this model. Thomas *et al.* (2004) created a baseline FCS from a $0.5^\circ \times 0.5^\circ$ spatial resolution average climate (1961-1990) (New *et al.*, 1999; New *et al.*, 2000) [<http://ipcc-ddc.cru.uea.ac.uk>] using identical rules to (Craig *et al.*, 1999), except that a minimum of four months of suitable transmission was required to define an annual FCS value for any grid cell throughout Africa. This avoided an FCS step artefact at the latitude of 8 degrees north. Thomas *et al.* (2004) then compared these to changes in future climate from the HadCM2 general circulation model, centred on the years 2025, 2055 and 2085. The $2.5^\circ \times 3.75^\circ$ (latitude by longitude) spatial resolution difference fields were resampled by cubic-spline interpolation to $0.5^\circ \times 0.5^\circ$ spatial resolution and added to the baseline from which the FCS values were then recalculated. The authors did not detail changes in PAR and simply discussed spatial changes in FCS concluding that: “*climate change is unlikely to lead to the widespread expansion in the distribution of stable malaria in Africa during the next few decades*” (Thomas *et al.*, 2004).

For comprehensiveness, we mention a variant of the MARA model approach that has been used to predict changes in malaria seasonality in Africa under future climate change scenarios (Tanser *et al.*, 2003). We have chosen not to consider this work of Tanser *et al.* (2003) in detail, however, as significant methodological issues concerning its approach and validation have been raised

(Reiter *et al.*, 2004) and because the work is largely superseded by Thomson *et al.* (2004).

Note that all the studies reviewed above, whether statistical or biological, interpolate the coarse spatial resolution future climate predictions for comparison with their finer spatial resolution climatology baseline at some stage in their analysis process. This is a common, if not universal procedure in these studies, which disguises the crude spatial resolution of the HadCM3 AOGCM data. It has some generally unacknowledged implications that we investigate below by implementing four climate “case” studies with a single climate scenario (see section 4.2 and table 1).

4.2. Climate change impact methods

For this report the HadCM3 coupled atmosphere-ocean general circulation model (AOGCM) is used [<http://www.metu.gov.uk/research/hadleycentre/models/HadCM3.html>]. This AOGCM was developed at the Hadley Centre for Climate Prediction and Research of the United Kingdom’s Meteorological Office, and downloaded on 14 May 2005 [http://www.mad.zmaw.de/IPCC_DDC/html/SRES_TAR/index.html], this AOGCM has the same 2.5° x 3.75° (latitude by longitude) spatial resolution as HadCM2 (Hulme *et al.*, 1999; Gordon *et al.*, 2000; Pope *et al.*, 2000).

We chose the medium-high A2 emission scenario. This choice has little consequence on the predictions as the difference between the projected impacts of emission scenarios before 2030 are small (Stott and Kettleborough, 2002). Since the HadCM3 AOGCM simulates weather, individual years can be noisy so that eleven year averages were used for future climate, centred on 2005 (2000-2010) for the baseline and 2015 (2010-2020 inclusive) and 2030 (2025-2035 inclusive). Moreover, we have also chosen to use the average of the A2a, A2b and A2c ensemble member runs, each of which were started with very small differences in their initial conditions, so that the ensembles could be merged to

obtain a more representative climatology. The HadCM3 AOGCM data are provided as actual future climate values rather than difference fields, as were available for HadCM2. The relevant meteorological variables for calculating FCS, mean surface air temperature (K) at 2 metres, mean minimum air temperature (K) at 2 metres and total precipitation (mm/day) for the years 2000 to 2035 inclusive were obtained. These were then turned into FCS using the rules outlined in appendix 2.

In all the four case studies (see Table 4) we use the bicubic spline interpolation (ERDAS Imagine 8.7, Leica Geosystems GIS & Mapping, Atlanta, Georgia, U.S.A.). This is one of the most computationally intensive forms of interpolation, but it results in the most spatially accurate and smoothest output images and is thus most often recommended for ‘upsampling’ (Shikin and Plis, 1995). Note that for each of these climate change case study Figures, the maps are presented as follows: a) is the baseline FCS; b) is the 2015 FCS; and c) is b) – a); d) is a repeat of the baseline FCS; e) is the FCS in 2030; and f) is e) – d).

Table 1	Baseline	2015	2030
Case study 1	HadCM3 2005 2.75° x 3.75°	HadCM3 2.75° x 3.75°	HadCM3 2.75° x 3.75°
Case study 2	HadCM3 2005 10' x 10'	HadCM3 10' x 10'	HadCM3 10' x 10'
Case study 3	New 61-90 10' x 10'	HadCM3 10' x 10'	HadCM3 10' x 10'
Case study 4	New 61-90 2.75° x 3.75°	HadCM3 2.75° x 3.75°	HadCM3 2.75° x 3.75°

Case study 1 (Figure 1) shows what is observed when using the HadCM3 data for all periods without any spatial interpolation to emphasise the coarse spatial resolution of the AOGCM data. Case study 2 (Figure 2) is identical to case study 1, except that all data are interpolated to a 10' x 10' spatial resolution. Case study 3 (Figure 3) follows the canonical method of combining the coarse spatial resolution future predictions with a fine spatial resolution contemporary climatology. To do this we first implement the FCS rules (see Appendix 2) on a 10' x 10' spatial resolution global climatology for the 1961-

1990 period (New *et al.*, 2002) to define the baseline. The HadCM3 data are then interpolated to the same spatial resolution (see above for details on interpolation methods) from which the baseline is subtracted. In Case study 4 (Figure 4), we resample the baseline derived from New *et al.* (2002) to the same spatial resolution as the AOGCM data. In Figure 5 we illustrate the effects of the interpolation further by resampling the case study 3 baseline to a coarse $2.5^{\circ} \times 3.75^{\circ}$ (latitude by longitude) and back to a finer at $0.5^{\circ} \times 0.5^{\circ}$ and $10' \times 10'$ spatial resolution. No future climate data are used.

4.3. Climate change impacts results

All the climate change case study results are reported relative to the population recorded in 2005 with zero growth and no urban correction (see section 4). Note that, throughout all the results sections, PAR changes are summarized as the absolute total (and percentage change from baseline) in FCS classes 2, 3 and 4 since FCS 1 is no risk. Case studies 1 and 2 reveal relatively few changes, with those that do occur concentrated at the fringes of the FCS risk distribution, both by latitude and altitude (Figures 1c, 1f and Figures 2c, 2f). For case study 1, PAR increases from 0.589 to 0.603 (+2.455% of baseline) and 0.617 billion (+4.808% of baseline) by 2015 and 2030 respectively (Figure 6a). For case study 2, PAR increases from 0.708 to 0.722 (+1.874% of baseline) and 0.731 billion (+3.255% of baseline) by 2015 and 2030 respectively (Figure 6b). Case study 3 shows rather more dramatic changes again concentrated at the fringes of the FCS risk. PAR increases from 0.638 to 0.722 (+13.075% of baseline) and 0.731 billion (+14.495% of baseline) by 2015 and 2030 respectively (Figure 6c). Case study 4 returns more modest impacts. PAR increases from 0.598 to 0.603 (+0.841% of baseline) and 0.617 billion (+3.157% of baseline) by 2015 and 2030 respectively (Figure 6d). Note that the difference in PAR estimated between case studies 1-4 (2005 average 0.633 (range 0.589-

0.708) billion) is in the same order of magnitude (~20%) as the predicted impacts of “climate” change between 2005 and 2030.

4.4. Climate change impacts discussion

Case studies 1 and 2, in comparison with case study 3, serve to illustrate that, while changes look impressive, it is impossible to know if these differences result from any, or all, of the following: (i) using a different climate source for the baseline; (ii) using a 1961-1990 average for this baseline compared with shorter averaging periods for the future; (iii) the interpolation process; and (iv) climate change. It is not clear how these effects can be disentangled. This leaves the difficult problem of choosing the case study with which to try and determine demographic effects and calculate PAR changes. If we use the canonical method (case study 3) we get a more accurate representation of contemporary PAR, but future changes with an unknown level of change contributed by interpolation and other artefacts. If we use only the climate predictions, either at their coarse (case study 1) or interpolated spatial resolution (case study 2), we control for using a different climate surface and interpolation and perhaps get a more realistic measure of the changes, but the outcome is also a modelled and less robust picture of current PAR. Case study 4 uses the best climate information we have today but interpolated to the same spatial resolution as the climate predictions. It illustrates, therefore, a further defensible alternative.

It follows from these considerations that it is particularly difficult to be informed about changing numbers of people in epidemic prone areas, simplistically, those living in FCS class 2, since these populations are located at the altitudinal and latitudinal extremes where the methodological artefacts will be most concentrated. In addition, we believe that these methodological problems preclude reviewing country-based PAR change estimates, although these data are provided in a digital appendix that accompanies this report.

These artefacts will be an unresolved problem, generic to all climate change impact studies that compare coarse resolution futures with high spatial resolution derived from other sources. Figure 5 emphasises this by simply interpolating the baseline of case study 3 to a coarse spatial resolution and then interpolating back to finer spatial resolutions. All the changes observed are, therefore, due to the interpolation process alone and, not surprisingly, are again concentrated at the altitude and latitude fringes where the spatial rate of change of FCS is greatest (Figure 5).

It is perhaps too obvious to state that improving the spatial resolution of climate projections is critical to improving the scale at which we can resolve impacts. Other concerns include unexplained local variation in pixels, due to other malaria drivers operating at finer spatial scales (Thomas *et al.*, 2004; Snow *et al.*, 2006). We explore one example of these in the next section: population growth. As we have done with the climate change impacts, we first investigate demographic changes in a hypothetical world without climate change.

5. POPULATION GROWTH IMPACTS ON MALARIA

5.1. Population growth impacts review

The rate of human population growth is not known with certainty (O'Neill *et al.*, 2001), leaving considerable room for debate on the future size of the global population (Alho, 1997; Lutz *et al.*, 2001). The traditional approach to cope with uncertainties in population growth rates has been to frame plausibility boundaries as “scenarios”. There are sound statistical arguments for adopting a probabilistic forecast paradigm that more intelligently handles this uncertainty (Lutz *et al.*, 2001; O'Neill, 2004; O'Neill, 2005). This is done by estimating the likelihood of a given scenario based on the probability distributions derived from thousands of similar iterations of these same demographic scenarios. For simplicity, we review the most widely used of the deterministic forecasts

provided by the United Nations (see Appendix 3), although the U.S. Census Bureau (USCB, URL: <http://www.census.gov>), The World Bank (URL, <http://www.worldbank.org>), the International Institute for Applied Systems Analysis (IIASA, URL: <http://www.iiasa.ac.at>) and the Population Reference Bureau (PRB, URL: <http://www.prb.org>) all provide alternative global population projections that could have been used.

In brief, the UNPD-WPP database provides population scenario data as national, level inter-censal growth rates by quinquennium (five year period) so that population estimates can be projected, on a country by country basis, to any other year between 2000 and 2050 (U.N., 2005). Urban and rural divisions in population growth rates are currently not provided on-line as a range of high-, medium-, low- and constant fertility scenarios, as is the case with the national aggregate data (U.N., 2003). Thus, in choosing to look at the future impact of urbanization in this study, we have sacrificed the ability to investigate different population growth scenarios. Exploring the impacts of the UNDP-WPP and population growth scenarios from other organizations (O'Neill *et al.*, 2001; O'Neill, 2005) will be the object of future investigations.

5.2. Population growth impacts method

We have used population data from the Gridded Population of the World (GPW) version 3.0 (Balk *et al.*, 2006). GPW v3 is a global human population distribution map derived from areal weighting of census data from 364,111 administrative units to a 2.5' x 2.5' spatial resolution grid. Each grid cell represents the residential population count for the year 2000. This surface was projected in a stepwise manner to provide populations for 2005, 2015 and 2030. First, the existing surface was classified into urban, peri-urban, rural 1 and rural 2 classes based on previously-determined population densities for these areas (Hay *et al.*, 2005a) using population densities surrounding the largest urban agglomerations in the continent. This method is defined in detail in Appendix 4.

Urban growth rates were applied to the urban and peri-urban classes and rural to the rural 1 and rural 2 classes. The growth rates were obtained from the World Urbanization Prospects: The 2003 Revision, Population Database [<http://esa.un.org/unup/>]. These urban-rural extents were then redefined at 2005 using the newly derived population densities. The growth rates for the next five years were then applied. This progressed iteratively until population surfaces for 2015 and 2030 time periods were generated. The total African population for 2005, 2015 and 2030 was within 4.3, 4.9 and 4.0% of estimates of the UNPD-WPP [<http://esa.un.org/unpp/>]. In projecting populations in this way, we have also defined the urban-rural status of future populations based on their contemporary population density characteristics. To aid visualization of these changes, these surfaces can be seen in Figure 7 for 2005, 2015 and 2030.

5.3. Population growth impacts results and discussion

The change in PAR from the case study 3 baseline due to medium variant population growth scenario with urban rural stratification is dramatic. PAR increases from the 0.638 to 0.781 (+22.426% of baseline) and 1.031 billion (+61.485% of baseline) by 2015 and 2030, respectively (Figure 8a). The impact of human growth in Africa, therefore, far outweighs even the most dramatic of the climate change impacts.

In addition to the different demographic scenarios available (see section 5.1), another considerable source of uncertainty, generally not considered in these SA exercises, is the spatial uncertainty in the baseline population surface. This can be considerable. It depends mainly on the date of the last census data used [<http://www.census.gov/ipc/www/cendates/>] and the spatial resolution at which these population census data are made available (Balk *et al.*, 2006). These themes are discussed in detail elsewhere (Hay *et al.*, 2004a; Hay *et al.*, 2005b).

Given the scale of impact of population growth relative to climate change, it would seem proportionate to put more effort into exploring the uncertainty structures associated with the population ‘denominators’ in such exercises.

These changes will obviously cause an increase in the size of the younger age-groups where the majority of malaria mortality is concentrated (Snow *et al.*, 2003; Snow *et al.*, 2006). Further exploration of the implications of these changes for the future burden of malaria disease is an obvious target of future work. Defining age proportions in these risk groups is relatively trivial using the projected population data. Estimating the future change in attributable risk with which to estimate morbidity and mortality rates, for a specific age cohort, in a specific FCS risk category, is, however, significantly more problematic. This is because educated guesses will have to be made about future changes in morbidity and mortality risk which will be influenced by a plethora of interacting drivers (Snow *et al.*, 2006).

6. URBANIZATION IMPACTS ON MALARIA

6.1. Urbanization impacts review

This section of the report relies heavily on a previous review (Hay *et al.*, 2005a). We are not the first to be concerned with urbanization and its impact on health (Harpham and Tanner, 1995; Birley and Lock, 1998; McMichael, 2001; Hinrichsen *et al.*, 2002; Woods, 2003) and, more specifically, parasitic (Mott *et al.*, 1990) and vector-borne (Knudsen and Slooff, 1992; Lines *et al.*, 1994) diseases, including malaria (Bruce-Chwatt, 1983; Gazin, 1991; Warren *et al.*, 1999; Robert *et al.*, 2003; Keiser *et al.*, 2004; Donnelly *et al.*, 2005).

Contrary to common perception, however, the health status of urban populations in Africa is notably and consistently improved compared to rural populations (Hay *et al.*, 2005a). These better health indicators in urban communities are reported with very few exceptions from demographic and

health surveys, which are structured specifically to derive nationally representative samples of the populations surveyed [<http://www.measuredhs.com>]. These benefits are thought to reflect a combination of enhanced access to preventative and curative services, which may be related to wealth, education and/or simple physical accessibility of health facilities.

Moreover, cities are not optimal places for malaria transmission (Hay *et al.*, 2005a). The most extensive set of investigations on the effect of urbanization on malaria epidemiology was conducted by Trape *et al.* in Brazzaville, Congo in the early 1980s (Trape, 1987a; Trape, 1987b; Trape *et al.*, 1987; Trape and Zoulani, 1987a; Trape and Zoulani, 1987b). This series of papers describes how Brazzaville's inhabitants were subject to lower anopheline biting rates, lower transmission intensities, lower parasite prevalence rates (PR) and lower malaria-specific mortality rates than rural Congolese.

These findings have been corroborated by more than thirty independent investigations in sub-Saharan Africa (Hay *et al.*, 2005a). There is clear evidence that urbanization reduces the diversity of anopheline species in an environment, their numbers, their survival, their infection rates with *P. falciparum* and the frequency with which they bite people. Thus, fewer people acquire malaria infection, get sick and/or die of its consequences in urban areas. The most common explanation is the lower vector densities resulting from a paucity of clean freshwater breeding sites. As has been eloquently detailed (Trape and Zoulani, 1987b), however, the process of urbanization effects changes in indices of mosquito and malaria abundance not only by eliminating open spaces for breeding, but also by increasing pollution of the remaining breeding sites, thus, limiting the dispersal opportunities for adult mosquitoes. Finally, with higher human densities, per capita exposure to potential infection also decreases (Smith *et al.*, 2004).

To our knowledge, there has been no attempt to predict the impact of urbanization on the future PAR of malaria in Africa. Here again, to study its effect, we first look at its impact on demographic changes in a hypothetical world in which climate change is controlled.

6.2. Urbanization impacts methods

The method by which urban and rural population stratifications are used here is outlined in a recent review of the effect of urbanization on malaria morbidity and mortality in Africa (Hay *et al.*, 2005a) and briefly summarized in Appendix 4. How the decision rules were generated to move PAR between risk classes according to their urban-rural status is then detailed in Appendix 5.

6.3. Urbanization impacts results and discussion

Urbanization reduces the PAR estimates on the population growth only scenarios. These urban corrected PAR estimates show increases from 0.627 to 0.758 (+20.876% of baseline) and 0.972 billion (+54.994% of baseline) by 2015 and 2030, respectively (Figure 8b).

Although urbanization trends decrease the impact of population growth on PAR, these decreases in risk are not enough to affect it increasing to almost a billion people in the next 25 years.

7. INTEGRATED IMPACTS

7.1. Integrated impacts review

The only integrated study to date has been reviewed (van Lieshout *et al.*, 2004) in section 4.1.

7.2. Integrated impacts methods

Here we combine all the climate change, population growth and urban risk reduction effects to look at the composite picture on PAR outcomes in the next 25 years. Although we present the results for all of the climate change case studies and re-emphasise the previous caveats, we take a consensus path, using case study 3 as our current best guess at the future and elaborating more fully on the changing PAR by FCS class. It follows from the way we have structured our previous results, that we can loosely interpret what proportion of these changing PAR estimates are due to ‘climate change’, population growth and the mediating effects of urbanization.

7.3. Integrated impacts results

For case study 1, PAR increases from 0.537 to 0.753 (+40.348% of baseline) and 0.903 billion (+68.231% of baseline) by 2015 and 2030 respectively (Figure 9a). For case study 2, PAR increases from 0.687 to 0.865 (+25.839% of baseline) and 1.146 billion (+66.795% of baseline) by 2015 and 2030 respectively (Figure 9b). For case study 3, PAR increases from 0.626 to 0.865 (+38.006% of baseline) and 1.146 billion (+82.922% of baseline) by 2015 and 2030 respectively (Figure 9c). For case study 4, PAR increases from 0.588 to 0.753 (+28.044% of baseline) and 0.903 billion (+53.483% of baseline) by 2015 and 2030 respectively (Figure 9d).

Further investigation of the integrated climate change case study 3 shows FCS class 1, populations at no malaria risk, changing from 0.223 billion in 2005 to 0.187 billion (-16.133% of baseline) in 2015, and to 0.244 billion (9.252%) by 2030. FCS class 2, populations exposed to marginal risk, change from 0.065 billion in 2005 to 0.085 billion (30.155% of baseline) in 2015 and to 0.088 billion (36.130% of baseline) by 2030. Those suffering acute seasonal transmission in FCS class 3, changed from 0.153 billion in 2005 to 0.259 billion (69.532% of baseline) in 2015 and to 0.490 billion (221.267% of baseline) by

2030. Finally, those exposed to stable endemic transmission, FCS class 4, changed from 0.409 billion in 2005 to 0.522 billion (27.511% of baseline) in 2015 and to 0.568 billion (38.825% of baseline) by 2030.

7.4. Integrated impacts discussion

It is difficult to overstate the enormous impact of population growth. Malaria is the subject of two United Nations targets: the Roll Back Malaria (RBM) initiative which aims to halve malaria deaths and disability by 2010 (W.H.O., 1999); and the Millennium Development Goals (MDG) which aim to halt the rising incidence of malaria by 2015 (U.N.D.P., 2003). To contain this massive expansion of population in the face of continued malaria risk will be very difficult.

Moreover, the morbidity and mortality consequences of living at different levels of FCS risk are not linear. The balance of evidence is that there is an approximate doubling in both all-cause and malaria-specific mortality when moving from FCS 2 to classes 3 and 4 (Snow *et al.*, 2003). The concentration of the PAR increases in these FCS groups is, therefore, likely to have a significant effect on continental morbidity and mortality totals. As was argued in section 5.3, projecting changes in these classes will be non-trivial.

Integration of results does not imply the integration of errors. The numbers presented, as is common in such work, do not come with confidence intervals. This does not mean that these future PAR totals are known with precision. Providing credible ranges for these effects, based on an explicit probabilistic treatment of the uncertainty should be the single greatest component of future work in this area. Until this research is conducted, it is imperative to appreciate the tentative and preliminary nature of these conclusions.

This report is précised as a summary for policy makers (Section 1) and the main conclusions abstracted in a technical summary (Section 2).

8. FUTURE RESEARCH PRIORITIES

Almost no effort has been directed by the epidemiological and climate change research community at quantifying uncertainty in the PAR component of disease burden estimates. For example, no map of malaria risk (or the risks of any other disease) has been published with a spatial quantification of uncertainty, despite uncertainty modelling being a well-developed area of geographic information system research. These uncertainties compound with each dataset used to estimate population at risk and with measurement error, FCS, as well as human population distribution, information on its age composition and locations of urban rural divisions. These will obviously cascade as more assumptions are made about additional drivers and how they propagate into the future. To maintain the credibility of epidemiological cartography and the ability to estimate PAR it provides, it is important to develop a methodology to provide spatially explicit confidence intervals for these maps and their products.

It is clear that global environmental change will affect the epidemiology of malaria, regardless of any public health interventions that the international community may apply (Snow *et al.*, 2006). We have conducted a preliminary investigation into demography, climate change and urbanization. Evidence shows that land-cover and land-use change (deforestation, irrigation *etc.*) will also be critically important. It is possible that we might be able to quantify historical rates of change with the Landsat satellite data archive (Tucker *et al.*, 2004). This global, public-domain orthorectified data archive details land-cover at 30 x 30m resolution in the 1980s, the 1990s and 2000s. Moreover, in combination with cellular automata and land-use change models, these may be projected into the future (Claggett *et al.*, 2004; Jantz and Goetz, 2005). Developing and implementing these land-cover change models and combining them with demographic and climate change projections will provide a dynamic infrastructure for the evaluation of population at risk from 2005 to 2030.

In the absence of quantifying spatial uncertainties in estimates of populations at risk (and without anticipating how these will be influenced by trends in global change), monitoring and evaluating the impact of international investment on targets for malaria control in Africa will be extremely difficult. This is because it will be impossible to calibrate the confounding background change against which any intervention has operated. Providing a generic methodology for quantifying uncertainty in estimates of population at risk that is applicable to all vector-borne diseases, along with a platform for projecting changes in Africa with respect to demographic, land–cover and climate change pressures between 2005 and 2030, is therefore very important.

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10. GLOSSARY

<i>APfEIR</i>	Annual <i>P. falciparum</i> entomological inoculation rate. The number of <i>P. falciparum</i> positive mosquito bites per person per year (infected bites/per person/per annum).
Baseline	Contemporary climate from which change can be measured.
Climate	The expected average statistics of the weather at a given time.
Climate change	Change in the climate, externally driven from natural or man-made factors.
Climatology	The average climate, usually estimated from 30 years of observations.
Climate model	Process-based model of physical processes that determine the weather.
Climate variability	The expected range of possible weather at a given time.
FCS	Fuzzy climate suitability. Value between 0 and 1 defined as the suitability of local climate to support <i>P. falciparum</i> malarial transmission in an average year, where 1 is completely suitable and 0 completely unsuitable. See appendix 2.
PR	Parasite prevalence ratio. The proportion of a sampled population with <i>P. falciparum</i> parasites in their blood.
Peri-urban	Defined here as locations <1000 and >250 persons / km ² .
Rural	Defined here as locations <250 / km ² . This is further subdivided into rural 1 <250 and >100 persons / km ² and rural 2 <100 persons / km ² .
Urban	Locations >1000 persons / km ² .
UA	Urban agglomeration. Area with population within the contours of contiguous territory inhabited at urban levels of residential density without regard to administrative boundaries of 1 million inhabitants or more in 2003.

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Figure 1. Case study 1. Maps of climate change effects on FCS in 2015 and 2030 relative to 2005 baseline: no interpolation

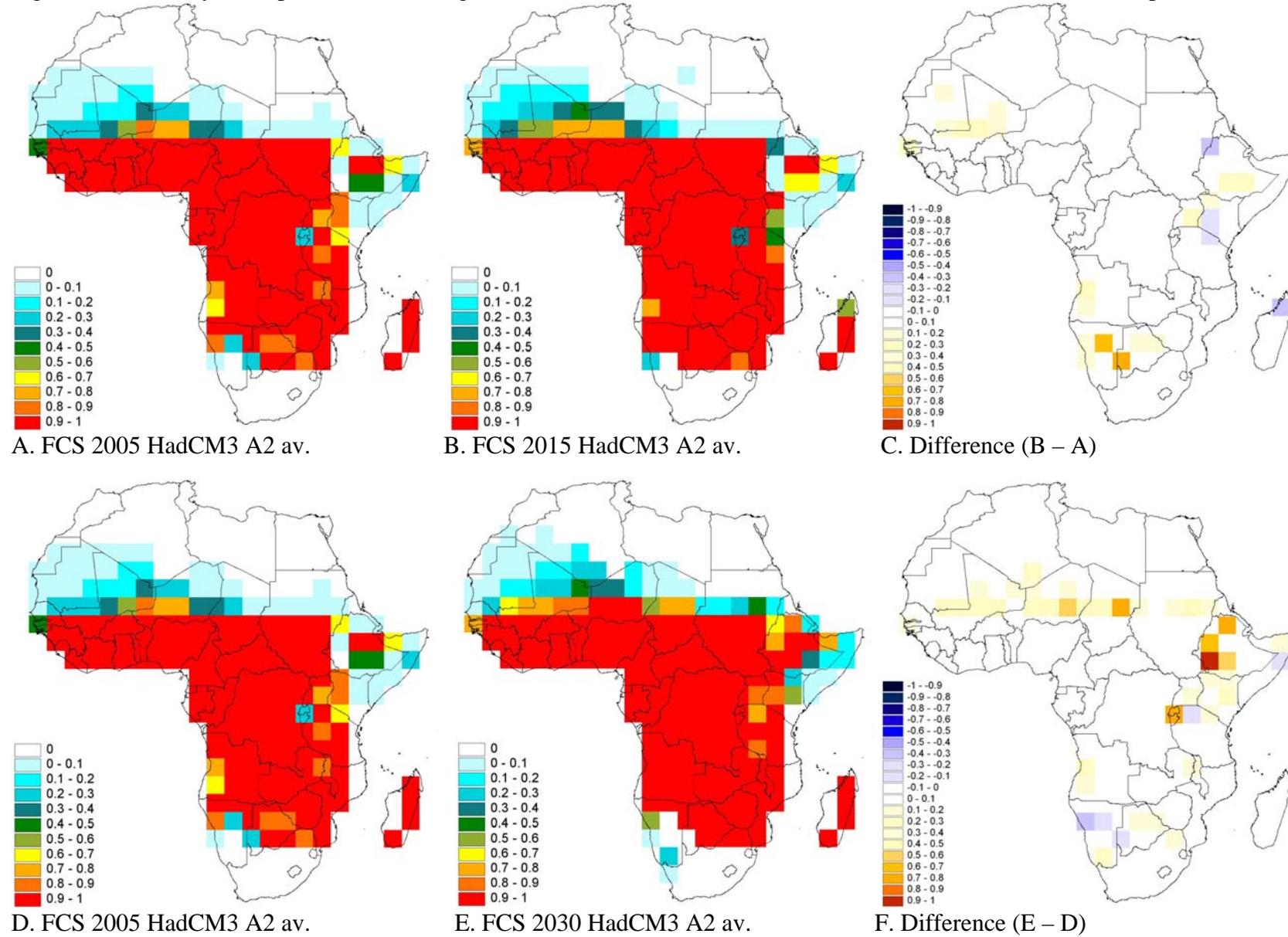


Figure 2. Case study 2. Maps of climate change effects on FCS in 2015 and 2030 relative to 2005 baseline: with interpolation

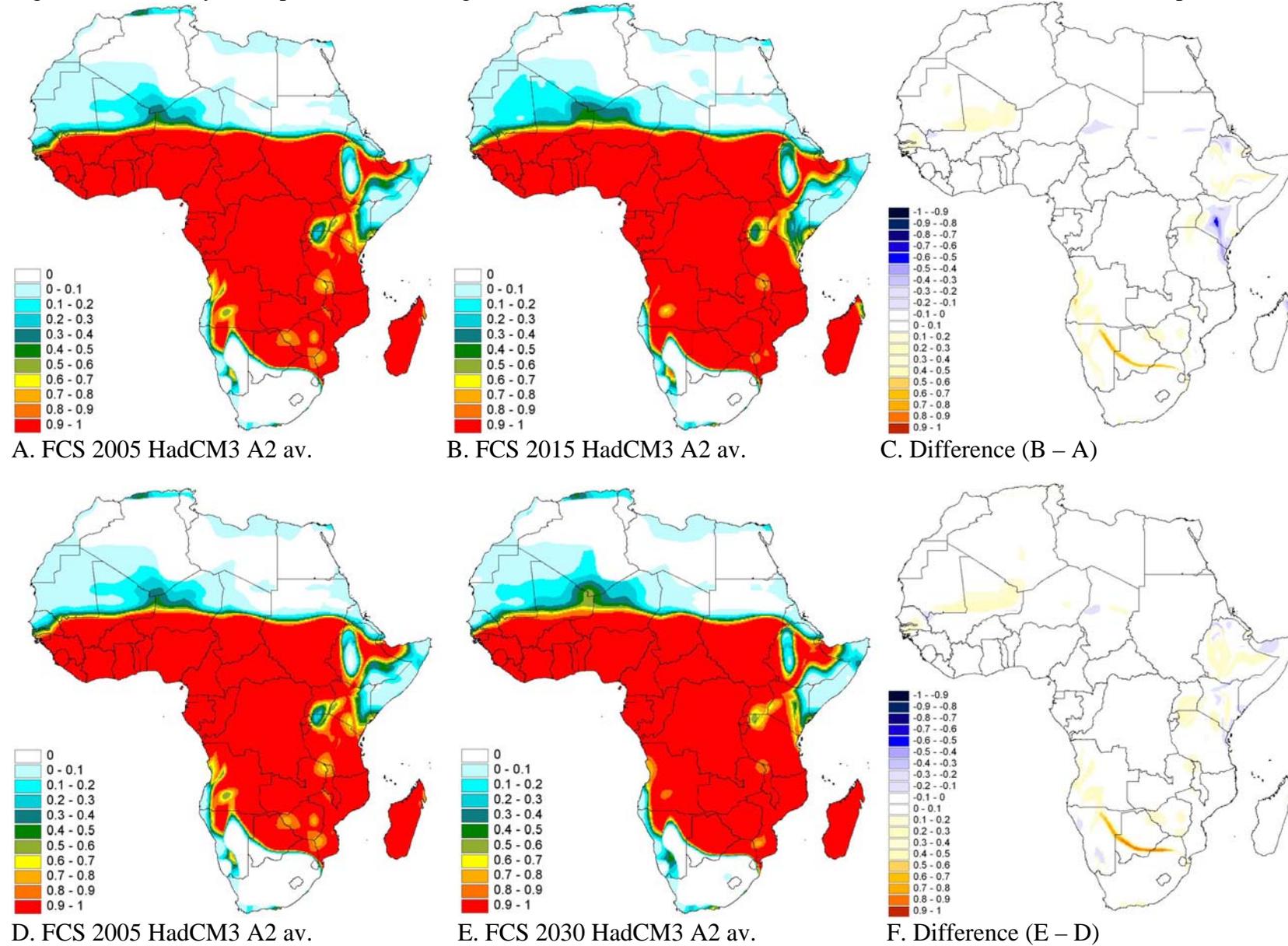
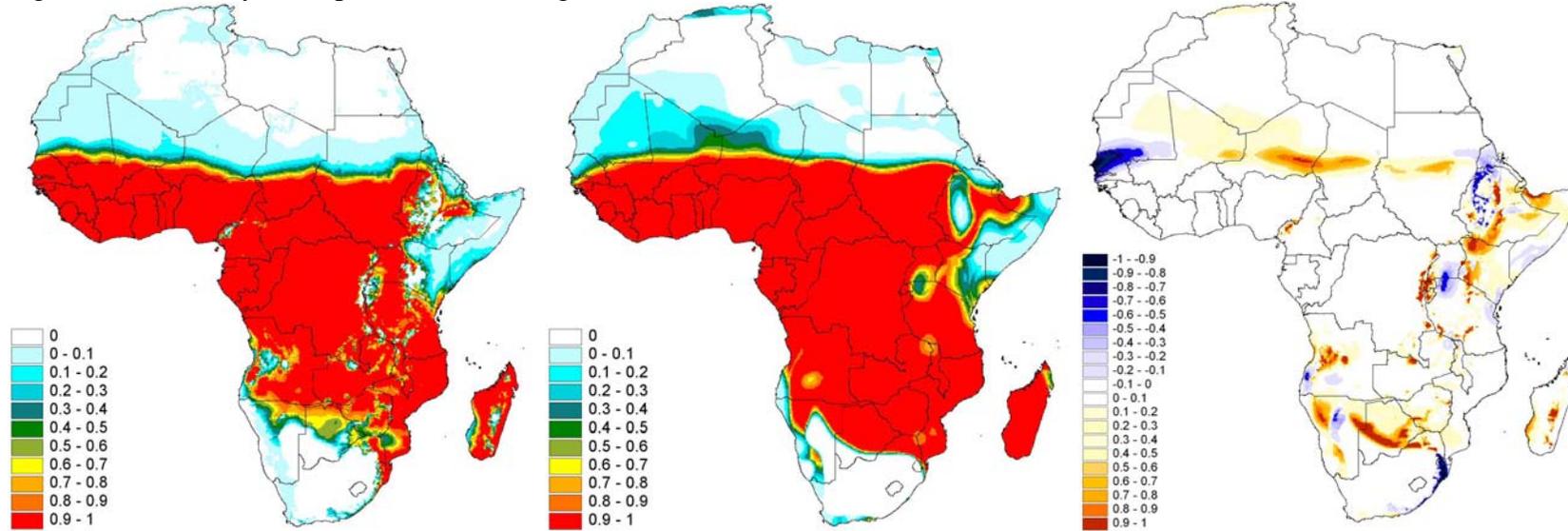
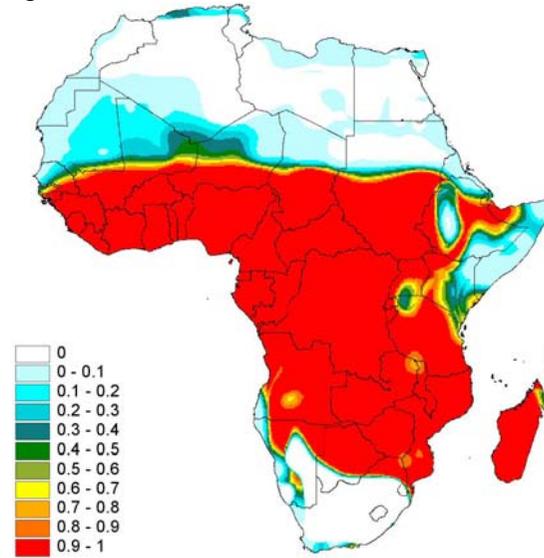


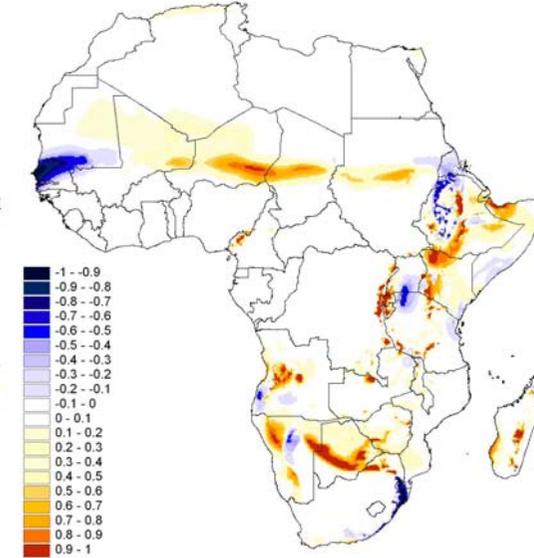
Figure 3. Case study 3. Maps of climate change effects on FCS in 2015 and 2030 relative to 1961-1990 baseline: at 10' x 10'



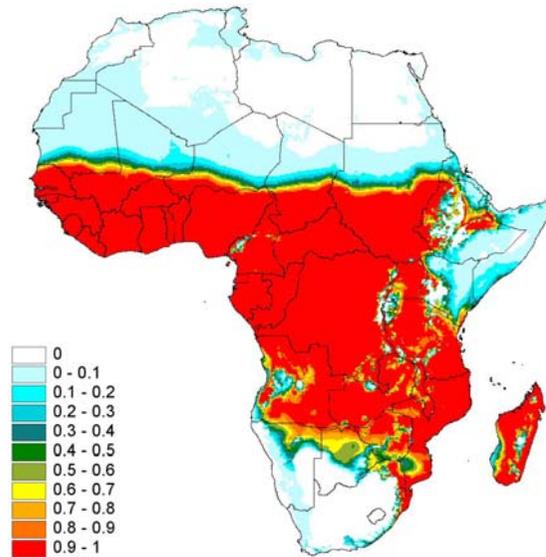
A. FCS 61-90 New et al.



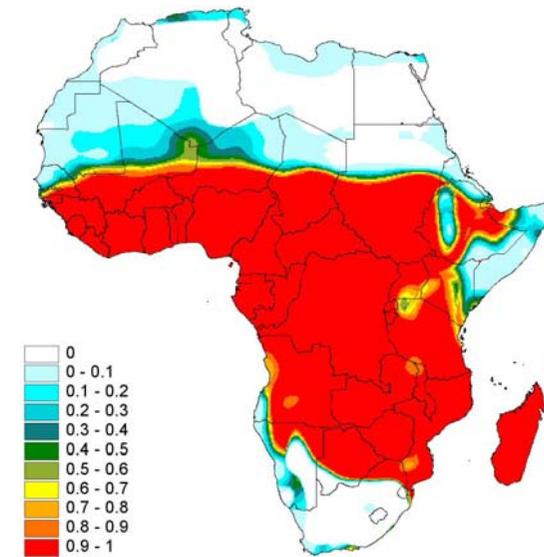
B. FCS 2015 HadCM3 A2 av.



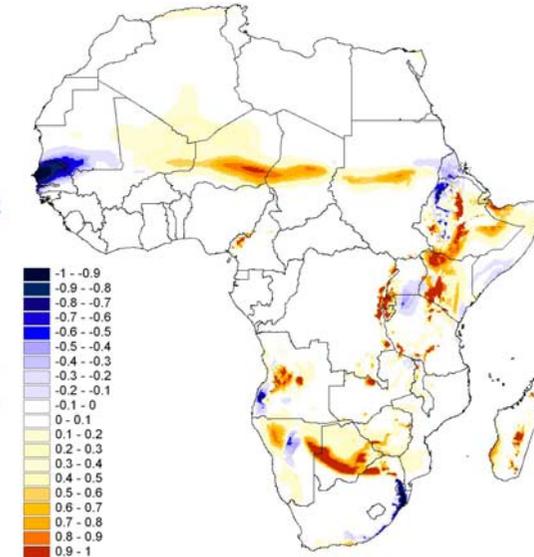
C. Difference (B - A)



D. FCS 61-90 New et al.



E. FCS 2030 HadCM3 A2 av.



F. Difference (E - D)

Figure 4. Case study 4. Climate change effects on FCS in 2015 and 2030 relative to a 1961-1990 baseline: at 2.75° x 3.75°

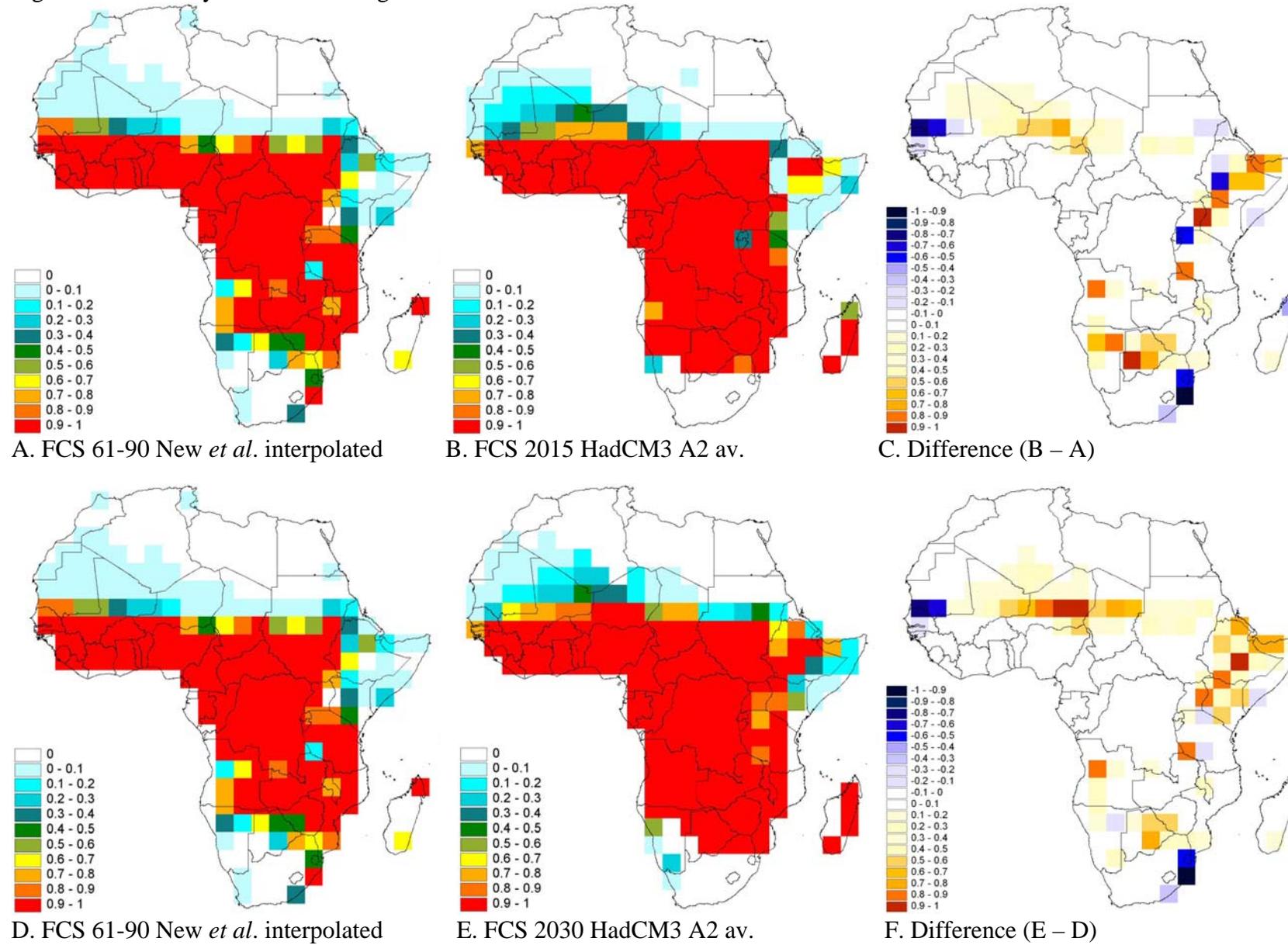
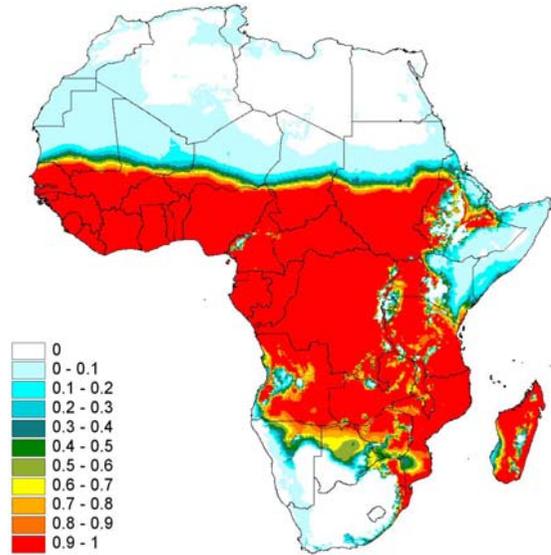
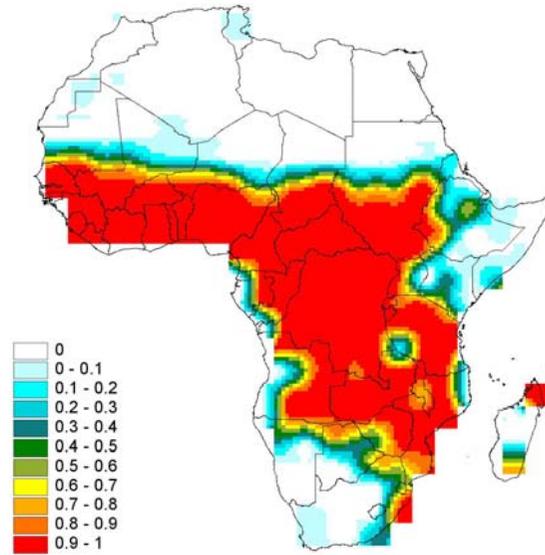


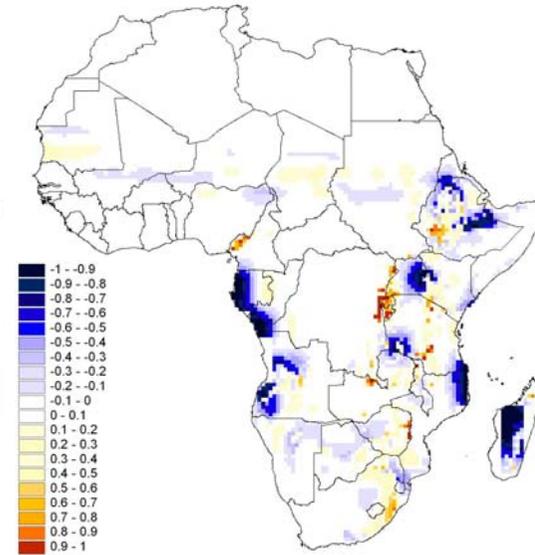
Figure 5. Maps to show the effect of spatial interpolation on FCS



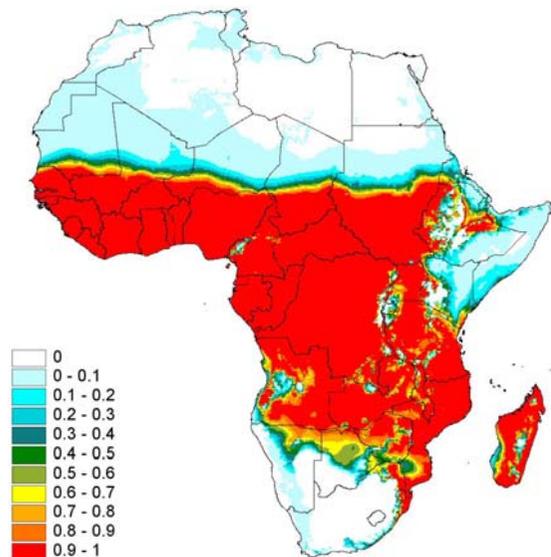
A. FCS 61-90 New et al.



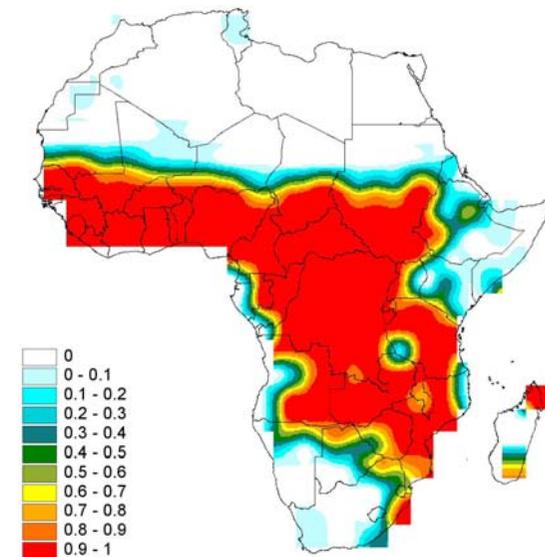
B. FCS 61-90 New et al. 0.5°



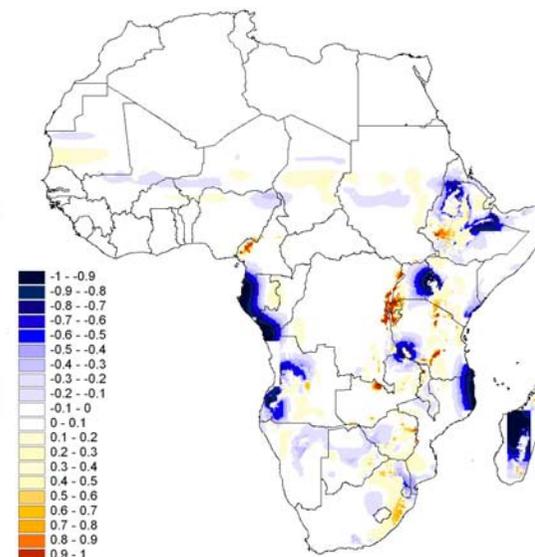
C. Difference (B – A)



D. FCS 61-90 New et al.

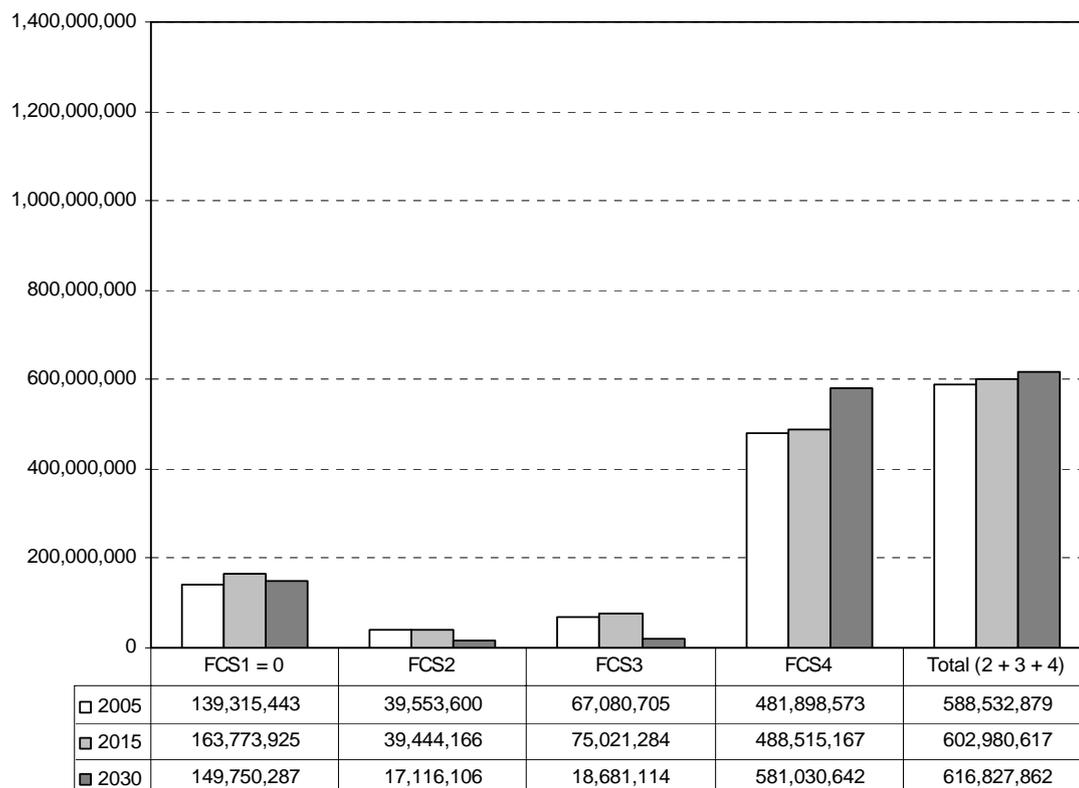


E. FCS 61-90 New et al. 10°.

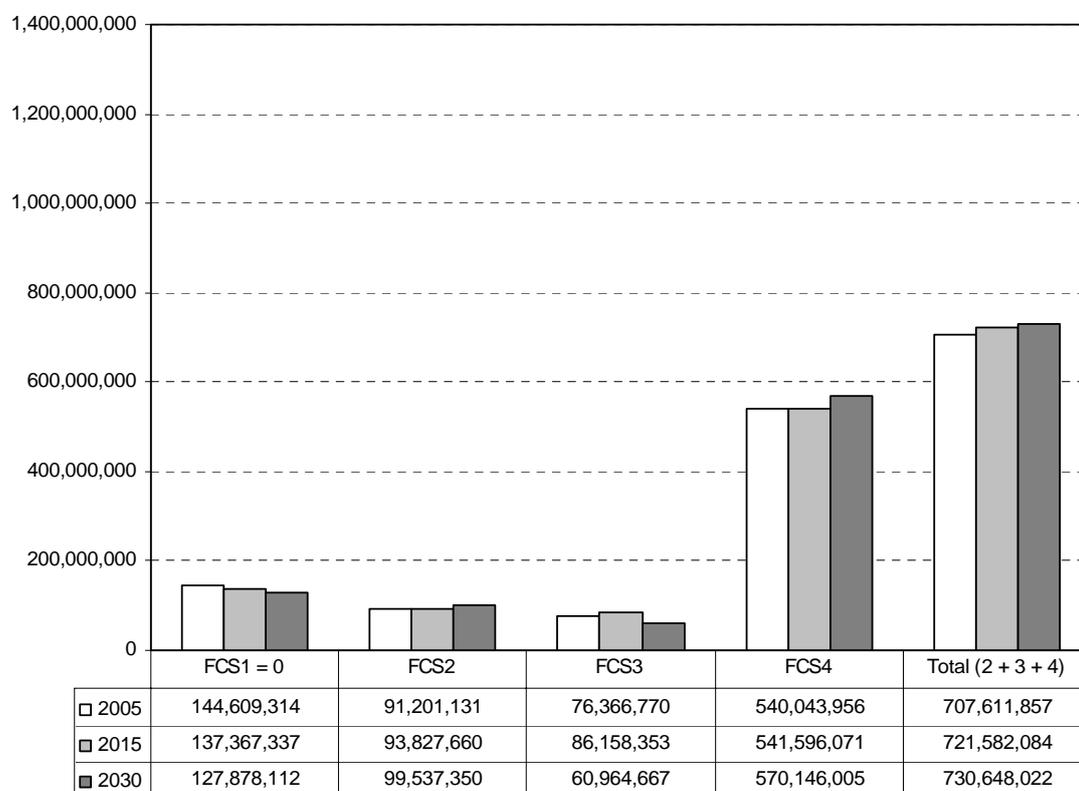


F. Difference (E – D)

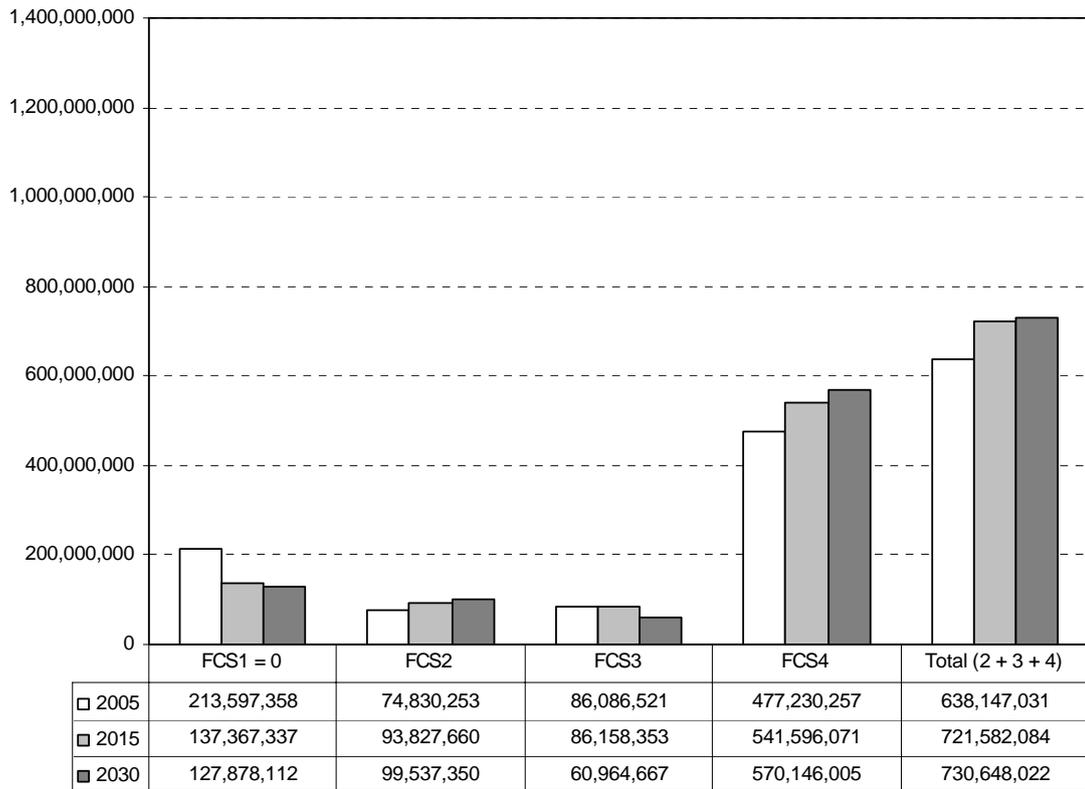
Figure 6. Bar plots PAR against FCS class relative to a constant 2005 population. Case studies 1-4 with no urban correction



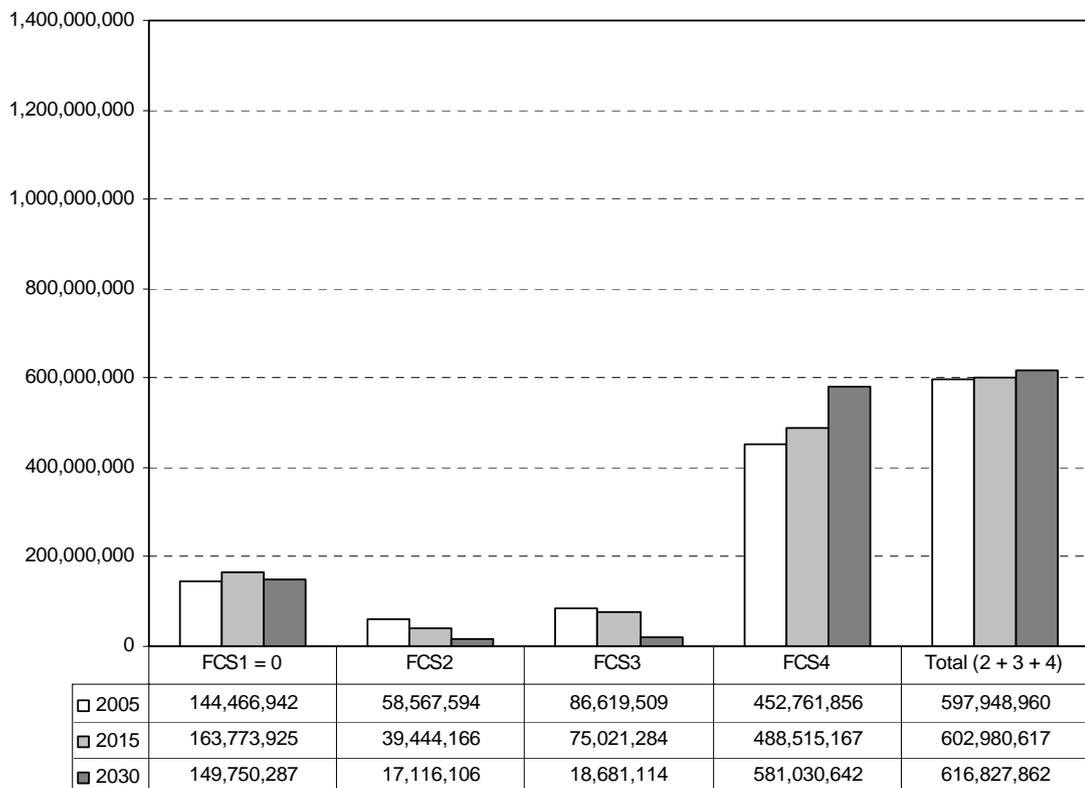
A, case study 1



B, case study 2

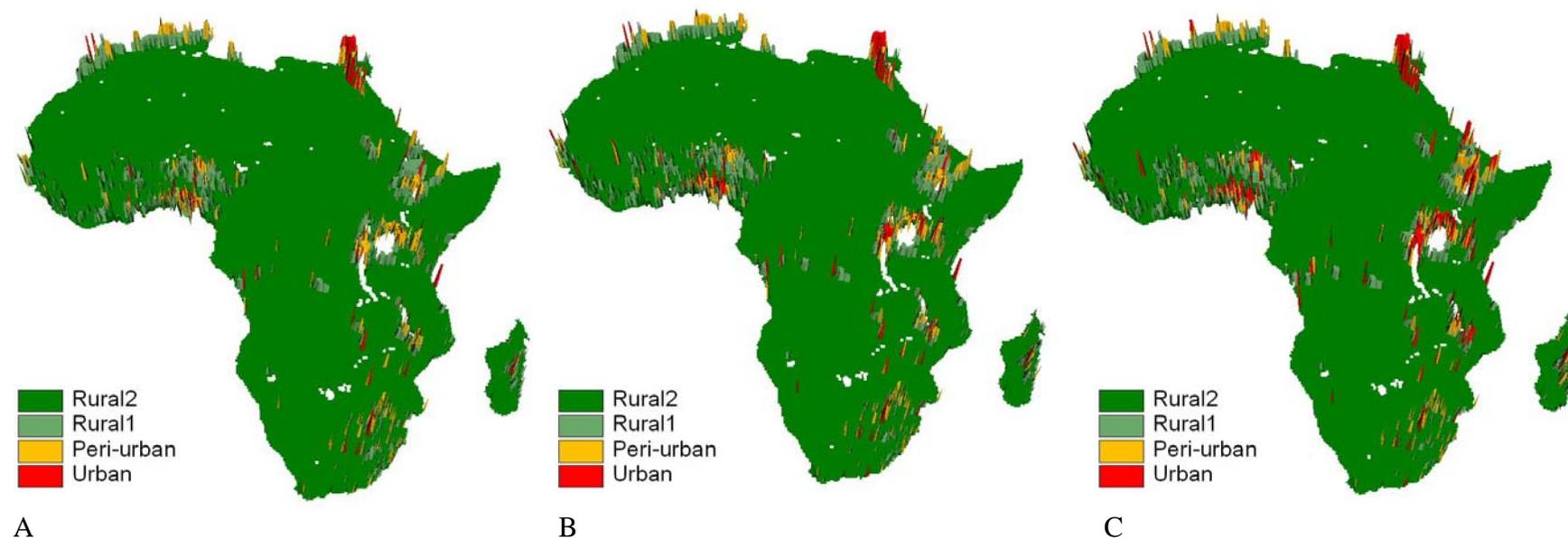


C, case study 3



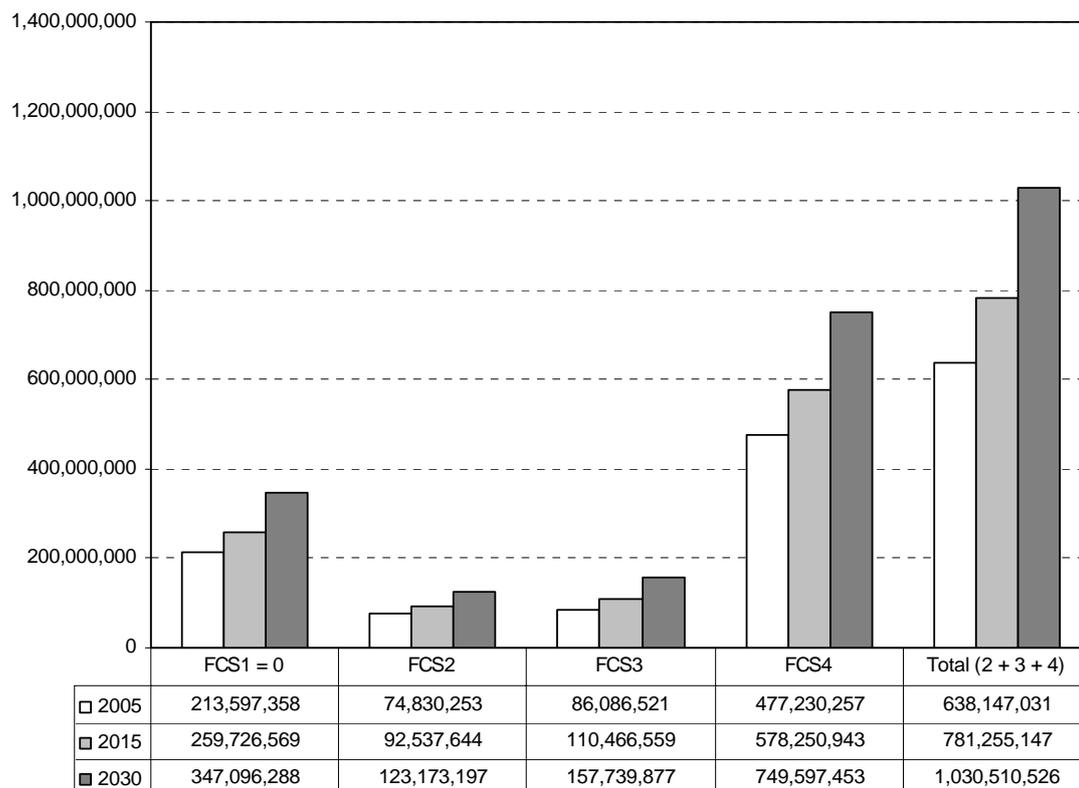
D, case study 4

Figure 7. Maps of urban rural stratifications inferred from population density projected to 2005 (A), 2015 (B) and 2030 (C). Total population in billions by land use type is provided in the table below (%)

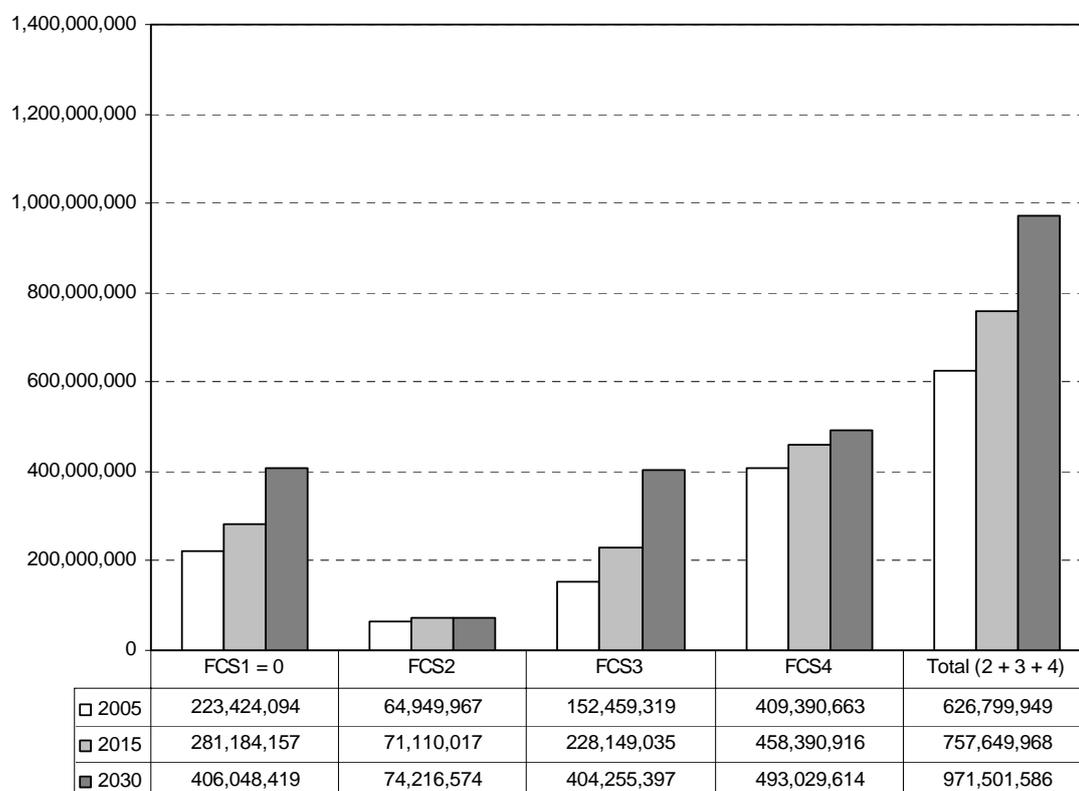


Land use	2005	%	2015	%	2030	%
Urban	182,068,400	0.210	310,013,824	0.292	634,812,800	0.452
Peri-urban	157,524,624	0.182	191,266,512	0.180	193,839,456	0.138
Rural 1	184,572,528	0.213	200,334,560	0.189	209,305,856	0.149
Rural 2	342,986,688	0.396	359,245,856	0.339	367,216,256	0.261
Total population	867,152,240	1.000	1,060,860,752	1.000	1,405,174,368	1.000

Figure 8. Bar plots of PAR changes by FCS class due to population growth uncorrected (A) and corrected (B) for urbanization in the absence of climate change

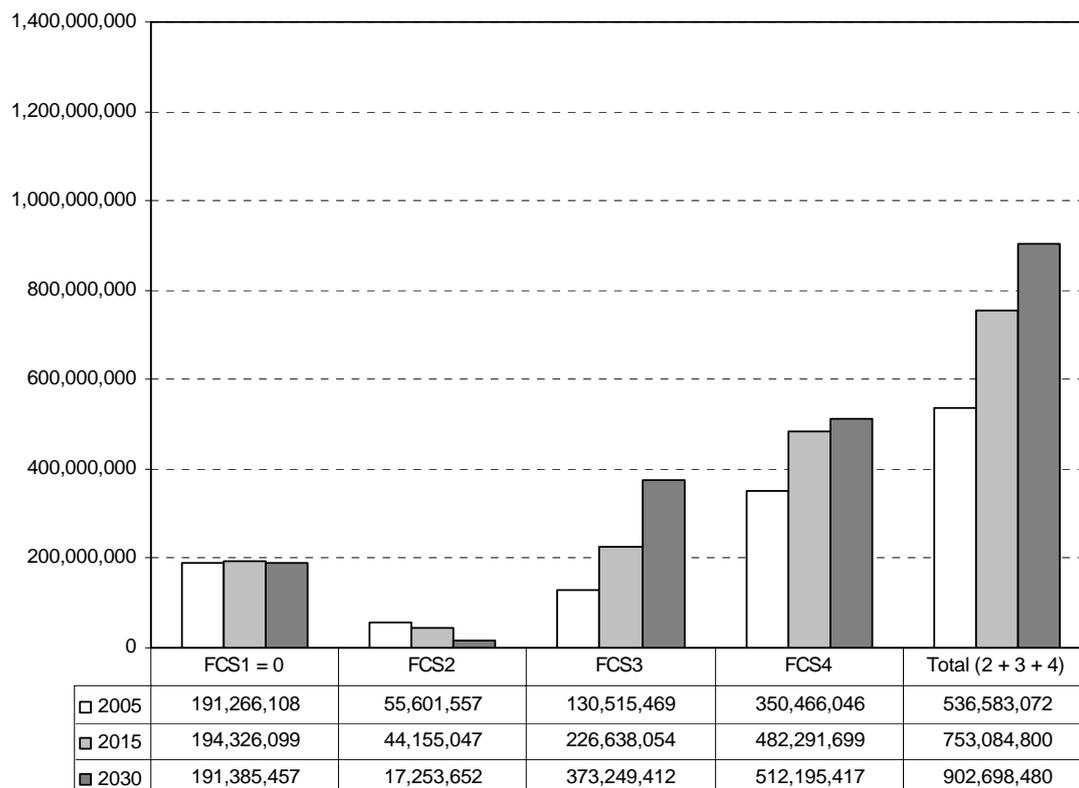


A

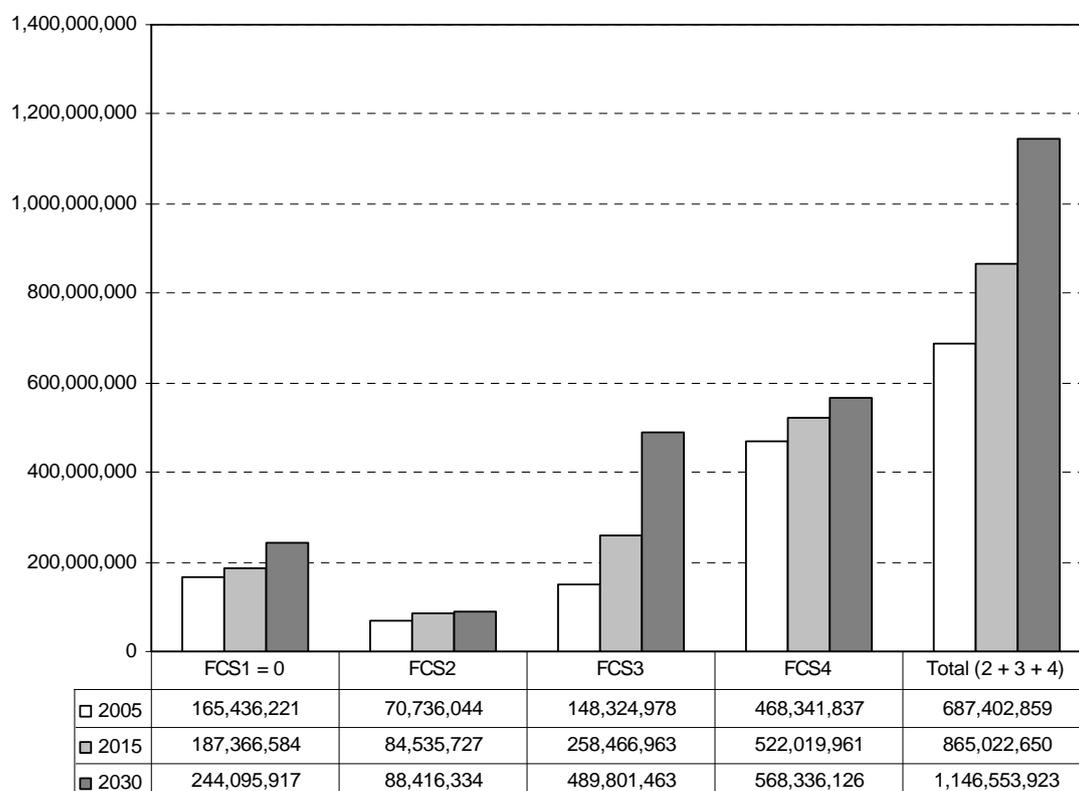


B

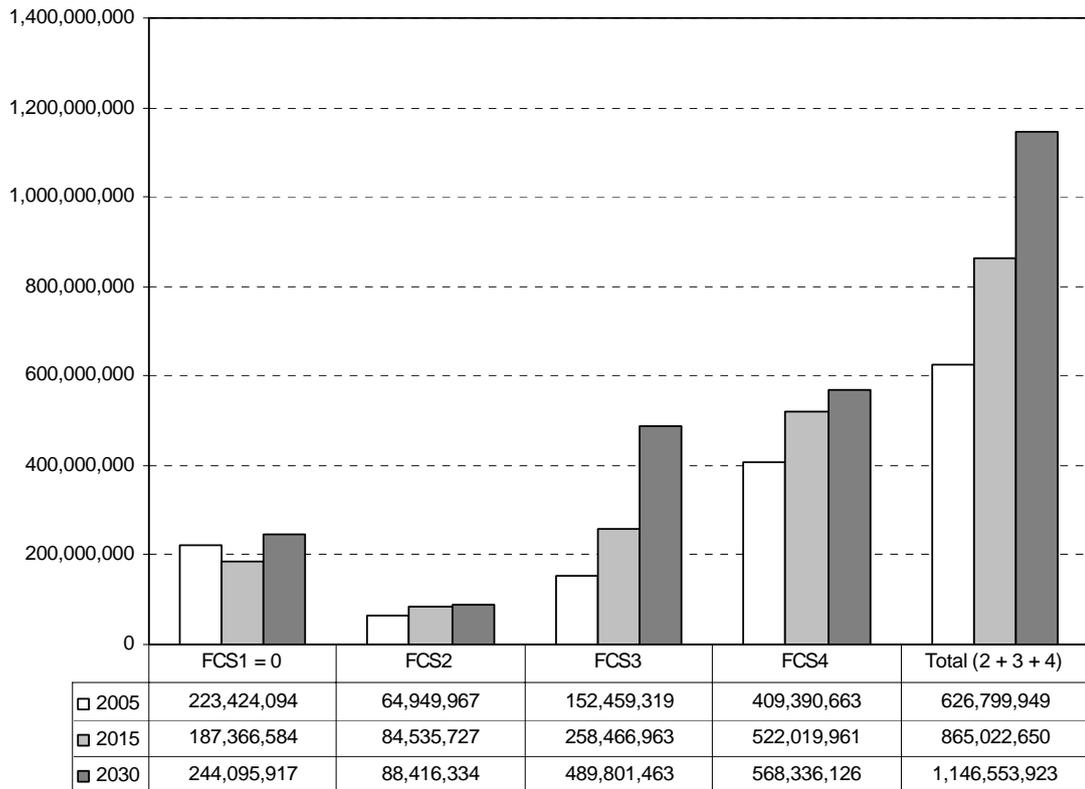
Figure 9. Bar plots of PAR by FCS for the integrated assessment. Climate change case studies 1-4 combined with population growth and urbanization



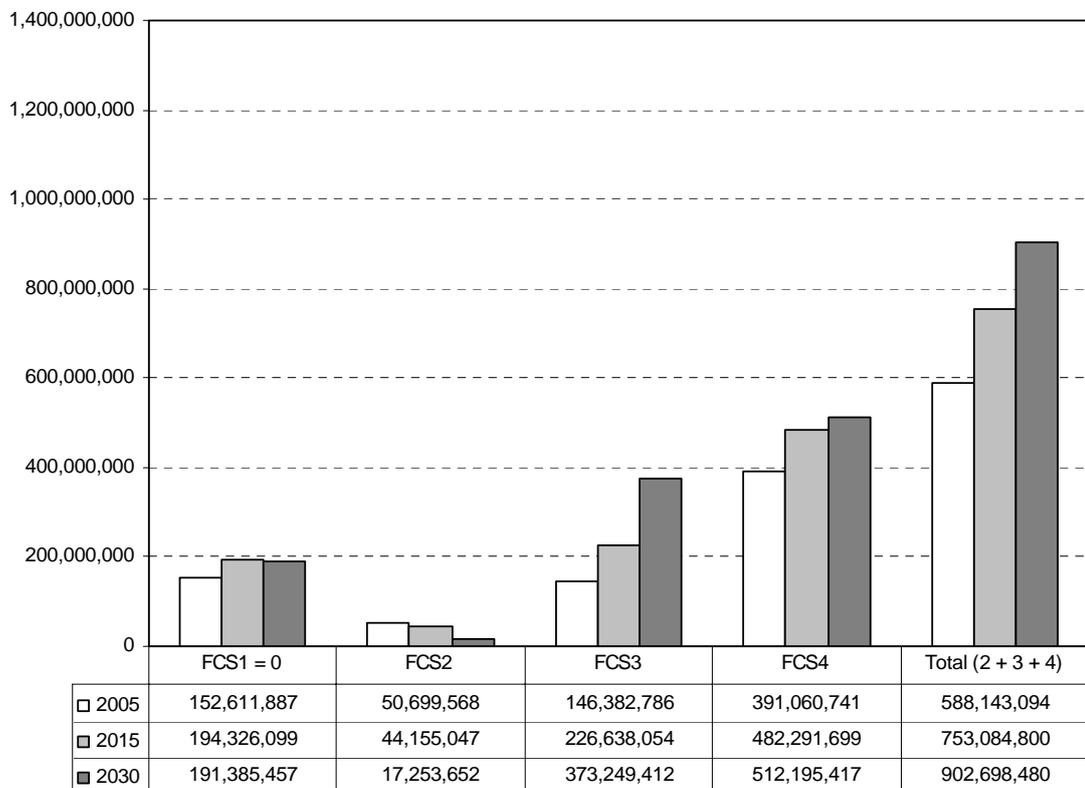
A, case study 1



B, case study 2



C, case study 3



D, case study 4

Appendix 1: Explaining location and spatial resolution

The most common way to define a place on Earth is with reference to its latitude and longitude. Horizontal divisions of latitude (or parallels since they are equidistant) are approximately 120 km apart (there is variation because the Earth is not a perfect sphere). Degrees of latitude are numbered from 0° to 90° north and south. Zero degrees is the equator, 90° north is the North Pole and 90° south is the South Pole. The vertical longitude lines (or meridians) converge at the poles and are widest at the equator, approximately ~120 km apart at the equator. Zero degrees longitude is located at Greenwich, England (0°). The degrees continue 180° east and 180° west where they meet and form the International Date Line in the Pacific Ocean. To precisely locate points on the Earth's surface, degrees longitude and latitude have been divided into minutes (') and seconds ("). There are 60 minutes in each degree. Each minute is divided into 60 seconds. Seconds can be further divided into tenths, hundredths, or even thousandths. Presenting this familiar system in two dimensions requires one to mathematically transform a curved surface into a flat one. It is obvious that this cannot be done without distorting or ripping the surface. Thus the spatial resolution conversion table provided below is an approximation, but should help the reader interpret spatial resolutions quoted throughout this document.

Degree	Minutes	Seconds	Km	m
5.00000000	300	18000	600	600000
3.75000000	225	13500	450	450000
2.50000000	150	9000	300	300000
1.00000000	60	3600	120	120000
0.50000000	30	1800	60	60000
0.16666667	10	600	20	20000
0.10000000	6	360	12	12000
0.08333333	5	300	10	10000
0.04166667	2.5	150	5	5000
0.00833333	0.5	30	1	1000
0.00416667	0.25	15	0.5	500
0.00104167	0.0625	3.75	0.25	250

Appendix 2: The FCS index for stable *P. falciparum* malaria transmission

We describe the MARA model (Craig *et al.*, 1999) in detail, as we use this as our index of malaria risk. The MARA model defines FCS as:

$$FCS = \cos^2 \left[\frac{(x - U)}{(S - U)} * \frac{\pi}{2} \right]$$

where x is a climate parameter, U is the value of x when conditions are unsuitable, and S is the value of x when conditions are suitable. When S is greater than U the suitability $(1-y)$ increases with x ; when S is less than U the suitability y decreases as x increases. The parameters U and S are given in the table 1 and their justifications can be found in the original paper (Craig *et al.*, 1999).

Appendix 2, table 2	Increasing curve	Decreasing curve
Mean diurnal air temperature (°C)	U = 18, S = 22	S = 32, U = 40
Monthly total rainfall (mm)	U = 0, S = 80	n.a.
Annual minimum temperature (°C)	U = 4, S = 6	n.a.

The model defines monthly increasing and decreasing curves for mean diurnal air temperature, a monthly increasing curve for rainfall, and a single increasing curve for annual minimum temperature (see table). For each month $m = 1, 2, \dots, 12$ the suitabilities yTm and yRm were calculated from the air temperature and rainfall constraints, respectively. Monthly suitability ym was then computed as $ym = \min(yTm, yRm)$. For each year, the suitability $yTmin$ due to annual minimum temperature was estimated using $Tmin = \min(Tm - 0.5DTRm)$. The suitability index for year t is defined as $MTCSI = \min(ymax, yTmin)$, where $ymax = \max(ym)$ persisting for a duration of three months poleward of 8 degrees north latitude and five months elsewhere.

This model is the most widely used malaria suitability transmission model for Africa (cited $n = 83$ times on 07 July 2005), and while imperfect (Snow *et al.*, 1996), has become the *de facto* standard for defining PAR for malaria morbidity and mortality estimates in Africa (Snow *et al.*, 1999; Snow *et al.*, 2003; Hay *et al.*, 2005a). FCS values vary between zero (totally unsuitable) to 1 (totally suitable) in an average year. For this report data are grouped into class 1 zero risk (FCS = 0), class 2 marginal risk (FCS >0 - <0.25), class 3 acute seasonal transmission (FCS >0.25 - <0.75) and class 4 stable endemic transmission (FCS >0.75) based on arguments around the relationship between FCS and PR and the FCS class (Omumbo *et al.*, 2004) and malaria morbidity and mortality expectations of populations living in such areas (Snow *et al.*, 2003; Hay *et al.*, 2005a). It is also important to note that the FCS does not take into account any effects other than climate and thus represents a biological optimum rather than a realized value.

Appendix 3: The UNPD-WPP global human population projections

The 2004 revision of the United Nations Population Division-World Population Prospects (UNPD-WPP) database [URL: <http://esa.un.org/unpp>] archives internationally mandated national population estimates and provides national resolution population projections as growth rates at five year intervals between 2000 and 2050. The UNPD-WPP assumes four possible future trends in fertility that are available online (U.N., 2005).

Total fertility in all countries is assumed to converge eventually toward a level of 1.85 children per woman (c.p.w.). Fertility in high-fertility countries (those with no fertility reduction by 2005) and medium-fertility countries (those with fertility decreasing but >2.1 c.p.w. by 2005) follows the fertility decline established by the UNPD on the basis of the past experience of all countries with declining fertility during 1950-2005. If the total fertility projected by a model for a country falls to 1.85 c.p.w. before 2050, total fertility is then held constant. In low-fertility countries (≤ 2.1 c.p.w. in 2005) fertility is assumed to remain below 2.1 children per woman and reach 1.85 children per woman by 2045-2050. For countries where total fertility was below 1.85 children per woman in 2000-2005, it is assumed that over the first 5 or 10 years of the projection period fertility will follow the recently observed trends in each country after which it increases linearly at a rate of 0.07 children per woman per quinquennium. Under the high and low variant scenarios, fertility is projected to remain 0.5 children above and below the fertility of the medium variant respectively. The constant-fertility assumption fixes fertility at the level estimated for 2000-2005. Mortality is projected on the basis of models of change of life expectancy produced by the UNPD. The selection of a model for each country is based on recent trends in life expectancy by sex. For the 60 countries highly affected by the HIV/AIDS epidemic, estimates of the impact of HIV/AIDS are made by explicitly modelling the course of the epidemic and by projecting the yearly incidence of HIV infection (U.N.A.I.D.S Reference Group on Estimates Modelling and Projections, 2002). The 2004 Revision incorporates for the first time, a longer survival for persons receiving treatment with highly active antiretroviral therapy. The future path of international migration is set on the basis of past international migration estimates and an assessment of the policy stance of countries with regard to future international migration flows. Mortality and international migration assumptions are held consistent between these population variants or scenarios.

As has been discussed (see section 5.1) many other human population growth scenarios are available but they have not been widely used in this area of research.

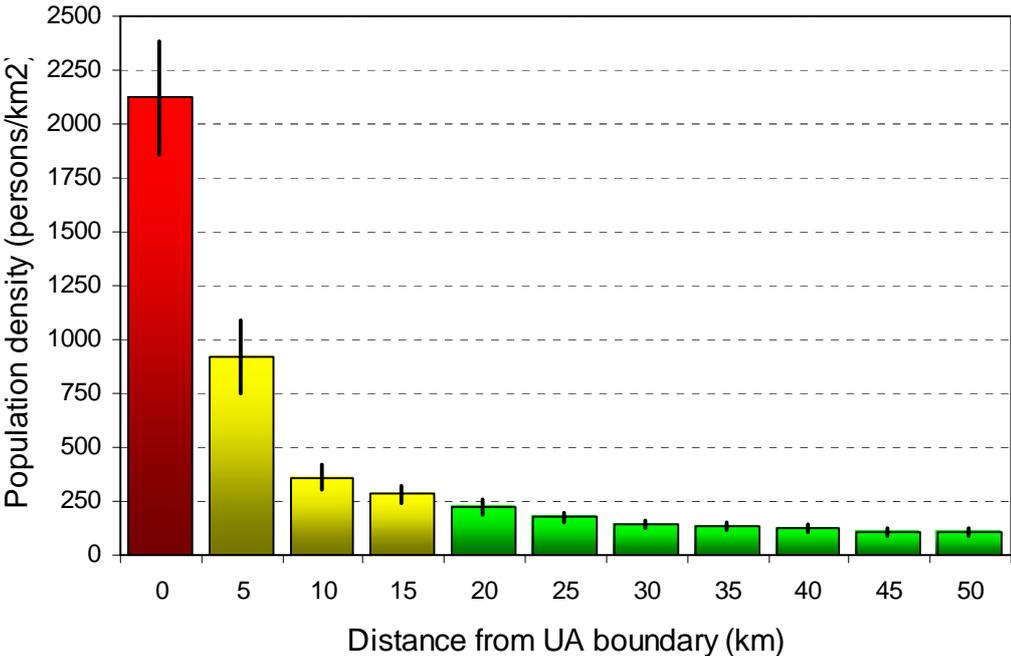
Appendix 4: Defining urban and rural populations at the continental scale

There is little consensus among national governments and international agencies on what constitutes an urban area or how to describe the process of urbanization. Thus, large-area statistics on urbanization rates obviously depend heavily on how urban populations are categorized in space and how these categorizations have changed over time (Hay *et al.*, 2005a). Recent advances in mapping urban extents make it easier to be objective and avoid inherent subjectivity in these definitions (Balk *et al.*, 2006). Here we use the global database of urban extents developed as part of the Global Rural-Urban Mapping Project (GRUMP) (Balk *et al.*, 2006). The GRUMP urban layer was developed at a 30" x 30" spatial resolution using data on night-time lights (NTL) and Landsat satellite sensor imagery, in combination with other geographic data. To date, it is the only global product of its kind released in the public-domain.

Numerous studies have shown that the blooming effect of NTL imagery causes an overestimation of urban area, however (Hay and Tatem, 2005; Small *et al.*, 2005). Moreover, in a specific validation exercise in Kenya, GRUMP and NTL data overestimated urban area consistently throughout the country (Tatem *et al.*, 2005). Due to the preliminary nature of these urban surfaces, and the problems of blooming, we outline a more conservative approach that uses the population density of the largest urban agglomerations (UA) as a surrogate. Africa had 37 UA with more than one million inhabitants in 2003 (U.N., 2003). These UA had on average 2.7 million inhabitants and accounted for 10% of the total population and 25% of the urban population in their respective countries. By isolating these UA on the GRUMP surface and overlaying them on GPW v3 it is possible to determine the population density "footprint" of these UA. (see appendix 4, figure 1).

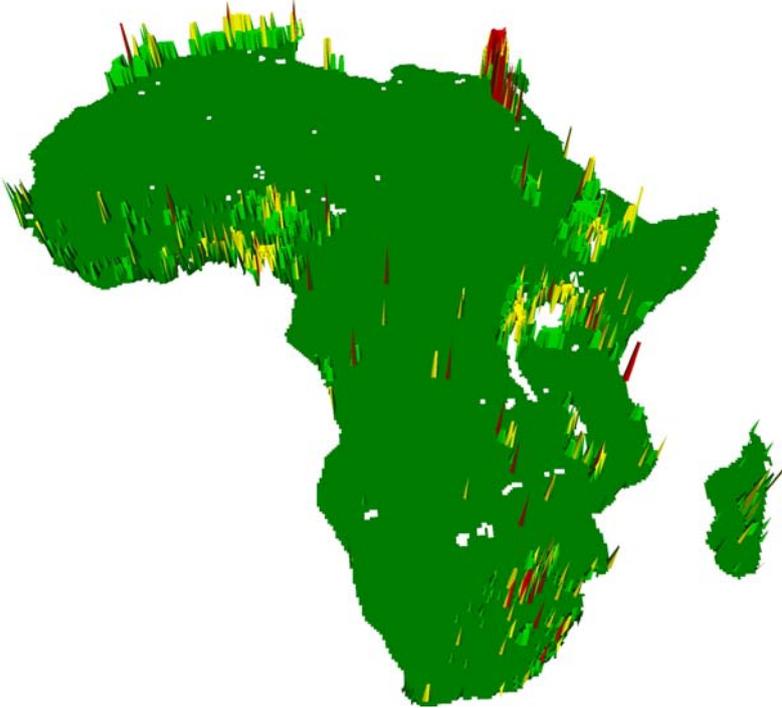
The appendix 4, figure 1 bar plot of the mean population density (persons / km²) in 2000 of the 37 UAs in Africa with more than one million inhabitants in 2003 (U.N., 2003) at successive 5 km buffers from UA edge. The GRUMP urban mask defined the spatial extent of the 37 UA. Overlaying this on GPW v3 allowed the population associated with these classes to be shown in the histograms: urban (red bars), peri-urban (yellow bars), rural 1 (light green bars) and rural 2 (dark green, off the scale). The core UA (defined by its GRUMP extent) have population densities >1000 persons / km²; peri-urban areas (between 5-15 km from the UA edge) <1000 - >250 persons / km² and rural areas (>20 km from UA edge) <250 persons / km². To guard against this rural stratification being biased towards high population densities (since we conservatively "train" population density on the largest African UAs) we further split the rural class into rural 1 (<250 - >100 persons / km² at >20 - <55 km from UA edge) and rural 2 (<100 persons / km² at >55 km from the UA edge). The vertical lines indicate the standard errors.

Appendix 4. Figure 1.



These population densities characteristic of urban, peri-urban and rural locations in Africa can be extrapolated across the continent using GPWv3 (see appendix 4, figure 2). The map is exaggerated vertically to help resolve small-area urban and peri-urban classes across Africa. This process identifies 0.2% of the African land-mass as urban, 1.1% peri-urban, 3.9% rural 1 and 94.8% rural 2 in 2000. These processed are iterated to 2005 and thence to 2015 and 2030 as outlined in section 3.2.

Appendix 4, figure 2. Population density classes plotted across Africa using GPW.



Appendix 5: A rubric for correcting FCS for urbanization

This appendix provides a summary of the method used to correct PAR for urbanization in sub-Saharan Africa outlined in a previous review (Hay *et al.*, 2005a). The standard approach to malaria burden estimates for Africa are generated by calculating the morbidity and mortality at intensively studied sites and associating these rates with malaria risk FCS classes since national registration systems for malaria morbidity and mortality are often inadequate (Snow *et al.*, 1999; Snow *et al.*, 2003). These FCS risk classes, human population distribution and urbanization have been mapped in Africa, so morbidity and mortality figures can be calculated across the wider continent and corrected for urbanization (Hay *et al.*, 2005a). Since PR is linearly related to the FCS values (Omumbo *et al.*, 2004) we should be able to simply investigate the relationship between FCS and a comprehensive database of PR data for Africa. At the time of compiling this report these information were not available to the authors, although and a substantial search effort has been funded to initiated its collation.

Therefore, a more circuitous route is required to investigate this urbanization–transmission affect in the interim. Previous work has demonstrated a strong logarithmic relationship between the annual *P. falciparum* entomological inoculation rate (*APfEIR*) and PR in a community (Beier *et al.*, 1999). We can therefore use existing *APfEIR* data (Hay *et al.*, 2000) to quantify the impact of urbanization on malaria transmission in Africa and thus its impact on PR and the FCS malaria risk classes with which they are associated. This has been completed (Hay *et al.*, 2005a).

First the largest meta-analyses of *APfEIR* data for Africa resulted in 233 temporally and spatially distinct *APfEIR* estimates from 22 countries between 1980 and 2004. Using the population density criteria for urban, peri-urban, rural 1 and rural 2 (FIG. 2b) the average *APfEIR* in urban areas was 18.8 (\pm S.E. 4.6) ib/p/a, peri-urban 63.9 (\pm S.E. 20.0) ib/p/a, rural 1 111.4 (\pm S.E. 28.4) ib/p/a and rural 2 141.1 (\pm S.E. 16.5) ib/p/a. Having quantified the reduction in *APfEIR* by urban and rural classes these can be projected onto the *APfEIR*-PR relationship (Beier *et al.*, 1999) to determine if the reduction in *APfEIR* effects PR to the extent that a population would move between FCS classes. The result is that peri-urban and rural 1 classes do not affect FCS significantly since the midpoint endemicity values do not move between FCS classes. The urban areas do, however, and on average lead to a reduction from class 4 to 3, NOT from class 3 to 2 and also from class 2 to 1. Note that this is possible due to the logarithmic nature of the *APfEIR*-PR relationship.

The decision rules are implemented on a categorical basis due to the inherent uncertainties in our ability to measure both parasite challenge (*APfEIR*) and parasite prevalence (PR). In addition, this *APfEIR*-PR relationship has recently been reinvestigated with a more detailed look at various theoretical models that have been suggested to describe this relationship (Smith *et al.*, 2005). Although

evidential support determined by a relative fits to the data was greater for biological models, since accuracy constraints force us to implement these decision rules categorically, the simple logarithmic relationship was maintained for the purposes of this report.

All the reports and papers produced within the Foresight project 'Infectious Diseases: preparing for the future,' may be downloaded from the Foresight website (www.foresight.gov.uk). Requests for hard copies may also be made through this website.

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