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SHORT TERM HEALTH IMPACT ASSESSMENT OF GLOBAL CLIMATE SCENARIOS ON URBAN SCALE

Roberto San José
Software and Modelling Group, Computer Science School, Technical University of Madrid (UPM), Madrid, Spain
roberto@fi.upm.es

Juan L. Pérez
Software and Modelling Group, Computer Science School, Technical University of Madrid (UPM), Madrid, Spain
jlperez@fi.upm.es

Libia Pérez
Software and Modelling Group, Computer Science School, Technical University of Madrid (UPM), Madrid, Spain
lperez@fi.upm.es

Rosa Maria Gonzalez Barras
Department of Physics and Meteorology, Faculty of Physics, Complutense University of Madrid (UCM), Ciudad Universitaria, 28040 Madrid, Spain
rgbarras@fis.ucm.es

Abstract

Climate change is projected to have effects on public health because citizens will be exposure to different levels of air pollution and temperature. There are few studies on health impacts of climate change with very high spatial resolution mainly due to issues in downscaling modelling and computational resources. This research tries to help understand the possible impacts of the global climate over the citizen´s health with 50 meters of spatial resolution covering the gap *between global/regional scale and urban scale. A computational dynamical downscaling modelling system has been implemented to assess the short term health effects of two global climate projections, IPCC 4.5 (stopping emissions increments) and 8.5 (no actions to stop emissions increments) over Milan and London area.. Modelled air quality concentrations at microscopic scale were compared with measurements of air quality stations, taking 2011 as the reference year; evaluation of modeling results determined that the system was suitable for the study objective. The results show that in the case of Milan the worst year for the effects of climate change on the health of citizens is 2050 for both scenarios but in 8.5 the highest increases are expected, especially in the area south east of the city that can reach 6.9%. The effect of temperature on health becomes 4 times more potent than exposure to concentrations of contaminants. In the case of London, the effects on the health of citizens of global climate change are marked by temperature increases, while decreases in mortality are expected from exposure to concentrations. Results of the modelling tool plus other impact assessment studies can be taken into account by the stakeholders to develop strategies to reduce the health impacts of the global climate on the cities.*

Keywords

Health impact, Climate Change, Air Pollution, Dynamical Downscaling

1. Introduction

Both air pollution and heat have adverse effects on the health of citizens, as demonstrated by episodes of high concentrations and/or high temperatures in which there is a dramatic increase in mortality and morbidity. At present, so that the majority of society is in agreement that climate change will have consequences on people's health, since some climate scenarios forecast an increase in the intensity and frequency of heat waves, as well as the number of pollution episodes in the atmosphere (Medina-Ramón and Schwartz 2007). Heat-/air pollution-related human mortality and morbidity is one of the important effects of climate change over people health (Confalonieri et al., 2007). Urban areas are particularly susceptible of these effects (Kinney et al., 2008). Urban areas of cities are the areas where climate effects are most important, cities are areas where the effects of the global climate change are important and very concentrated and therefore need to be analysed in detail. (Oleson et al. 2013), last researchers have found that climate change could have important effects on urban climate and urban air pollution concentrations (Mickley et al., 2004). Several epidemiological studies have demonstrated different effects of tropospheric ozone and particulate matter on human health, leading to an increase in mortality and daily morbidity. Negative health effects can be varied, but most studies focus on demonstrating health problems from cardiac and respiratory diseases as a result of exposure to high levels of air pollution (Burnett et al., 1997). Climate change is not only an environmental problem, it is a health and social large problem and researchers have to focus on to understand the climate impacts from different points of view to enhance mitigation and adaptation measures (Vesteri and Nontasak, 2018). It is necessary to research to better predict future impacts of climate change on health (Ostry en al., 2010). The majority of epidemiological studies concentrated on acute health consequences (due to short-term exposure). Also there are several large multi-city studies relating the numbers of hospital admissions with meteorological and air pollution exposure variables (Anderson et al., 2004).We focus on the direct impacts on the health of the citizens in the coming century with the effects of heat and air pollution concentrations. Climate change will affect the concentrations of air pollutants and their spatial distribution through various direct and indirect processes, such as changes in biogenic emissions, changes in the rates of chemical reactions between species, the heights of the mixing layer where the vertical movement of pollutants takes place, and changes in the patterns of atmospheric flow that drive pollutant transport in the atmosphere.

Climate-change projection from Global Circulation Models (GCMs) are increasing in resolution, but are still not appropriate from analysis health problems at urban scales. Global climate models generate information with a horizontal resolution of between 100 and 150 kilometers, this data is too coarse for city-level climate information. Local patterns of climate and air pollution are strongly influenced by the topography, land uses, buildings, etc. Therefore, in order to study the impact of climate on cities, very high spatial resolution data are needed to capture the high spatial and temporal variability of atmospheric variables in the city (Valari and Menut, 2008). Moving from large-scale climate projections to smaller spatial and temporal scales requires the application of downscaling techniques that bring additional information to bear on the area in question. Last advances in computer science and physics, especially in the downscaling techniques, have provided to the scientific community new approaches for investigating the effects of climate and air quality on the health of people living in cities. The key issue for health impacts related with the global climate is the use of high-resolution simulation models of future climate conditions over the cities and how the global climate boundary conditions may alter the local climate and air pollution conditions. During last years, only low-resolution data from global models existed. Therefore, high resolution climate models are needed. The resolution of global models has increased significantly. However, even the latest high-resolution simulations, at 25–50 km per gridbox, are unable to simulate all of the important fine-scale processes occurring at urban scales In this work is the first time that a regional/urban climate model is coupled with a computational fluid dynamic tool. Downscaling process can offer data about climate or air pollution at an optimal spatial and temporal resolution (Rosenzweig et al., 2010). The spatial resolution of the data produced by GCMs prevents them from being used directly as inputs to impact tools that aim to analyze how global climate changes can affect urban pollution in a city as well as its consequences on the health of citizens. At the technical level, there are two different approaches to obtaining finer resolution data from global climate data for the future: dynamic downscaling and statistical downscaling. Regional/urban numerical models (RCMs) on the specific area of interest are used in dynamic scale reduction and the boundary and initial data from the global climate mode are used as inputs for the RCM. RCM generates more detailed information at the regional level from GCM data, data is generated in response to a forcing of global data to finer inputs (topography, land use,...), in general RCM information is not fed back to the GCM. The statistical downscaling method derives relationships between variables based on observations from the past and then applies them to know the future climate situation. Its main additional value is that it is not require high performance computing as opposed to dynamic downscaling but its results are limited because relations established in the past do not have to be in the future. Moreover, it does not allow the generation of new variables as numerical models does.

In this case, we have developed a dynamical downscaling, using high-resolution, regional and urban climate and air quality state-of-the-art models. To take into account the effects of the buildings in the ventilation and shadow effects which are very important in the city simulation a Computational Fluid Dynamic (CFD) model is included in the in the simulation tool. Atmospheric circulation and therefore the climate of cities is influenced by urban structures such as buildings that increase atmospheric turbulence and so the transport of the pollutants is different by the presence of buildings (Piringer et al. 2007). CFDs are very demanding tools from a computational point of view, but they are developed following atmospheric physical laws and allow obtaining a full set of output variables that perfectly describe the situation of atmospheric pollution and climate in urban environments. This research was developed during DECUMANUS project (European FP7 program). DECUMANUS has provided a range of services aimed at urban managers that provide them with intelligent urban information to help them meet the challenges facing cities, including of course climate change. The main idea is that it is possible to adapt and mitigate the problems if they can be measured and understood and here it is where DECUMANUs services play an important function.

2. Material and methods

A health impact assessment with coarse resolution tend to substantially underestimate mortality/morbidity in large cities, so there is a gap between global climate data (coarse resolution) and local climate/air pollution data (fine resolution). In this study we propose a methodology to go from coarse resolution to urban resolution and how the high spatial resolution can be applied to know the possible health effects of the climate change on the citizens.This study produced quantitative and qualitative information about short term potential health effects of global climate on people over two European cities under two future climate scenarios. It comprises two elements. The first element, climate and air quality modelling, presents high-resolution (50 meters) simulations of present (2011) and future climate (2030, 2050 and 2100) over Milan and London (Kensington and Chelsea area) by dynamically downscaling global climate data using a regional and urban modelling system to generate locally meteorological and air pollution information. The second one, health impact assessment, quantifies the potential short term effects of the climate on human health. We have studied the impacts of two possible global climate scenarios on mortality and hospital admissions related with variations in the high temperatures and air quality. Health outcomes are based on dynamical downscaled information with very high horizontal resolution (50 meters) and one hour of temporal resolution. Short term health impacts were assessed for ozone (O3), particles with a diameter on the order of ~10 micrometers or less (PM10), apparent temperature (AT) and heat waves (HW). Future changes in these environmental exposure variables as simulated by the model system for future years and compared relative to conditions in the 2011. Concentration-response coefficients were taken from the recent environmental epidemiological literature.

2.1 Methodology

In this section we details the approach followed, including the description of the climate scenarios, the tool to make the dynamical downscaling tool and the health impact assessment module. The simulated periods correspond to non-continuous whole years, with the objective of capturing punctual events that, in case of simulating several consecutive yearly periods, the events could be smoothed or even cleared when performing the statistical average of several successive years. In our case we have selected three years of the future, 2030, 2050 and 2100 versus to the reference or present year that has been chosen, 2011.

2.1.1 Global climate scenarios

We have considered two Representative Concentration Pathways (RCPs), RCP 4.5 and RCP 8.5 (van Vuuren et al. 2011) defined by the IPCC (Intergovernmental Panel on Climate Change) institution in the Fifth Assessment Report (AR5). Four climate scenarios defined in the IPCC report (IPCC, 2013) are currently in use. These scenarios take into account different levels of pollutant emissions for the next years. These scenarios range from very strong (non-realistic) greenhouse gas emission mitigation scenarios (RCP2.6) to a "business as usual" emissions scenario (RCP 8.5) where emissions growth in the world. The two selected global climate scenarios are the most popular in the scientific community because these two scenarios represent low and high greenhouse gas emissions or radiative forcing projections respectively. Of four possible climate scenarios, two have been selected for reasons of computational demand. The choice is based on trying to show extreme changes between two possible future climatic scenarios, then we have chosen the worst-case scenario (RCP 8.5) and the most favorable (among the realistic ones) RCP 4.5, this choice will help us to know the possible impacts and be prepared for the application of mitigation and adaptation strategies. The scenario RCP 4.5 is characterized by radiative forcing stabilizing at 4.5 W/m2 by 2100 (Thomson et al. 2011), this scenario would be equivalent to an average global temperature increase of about three degrees Celsius. However, in the climate scenario RCP 8.5, no actions are taken to mitigate climate change and therefore it is considered the worst-case scenario, with the highest greenhouse gas emissions, which can cause an increase in global average temperature of up to six degrees (Riahi et al. 2011).

2.1.2 Dynamical downscaling tool

The spatial and temporal downscaling process, from 1º degree to 50 meters and from six hours to one hour, begins with the global climate projections produced from the global scale general circulation model CESM. We have utilized the Weather Research and Forecasting Chemical model (WRF/Chem) simulations driven by the outputs from the global climate models CESM through boundary and initial conditions. WRF/Chem (Grell et al., 2005) was applied in a one way nested approach, with an inner grid having a horizontal resolution of 1 km over the two cities and two outer grids having a horizontal resolution of 5 km and 25 km, this grid cover all

Europe. WRF/Chem is an online model which includes the chemistry and meteorological simulation, which means that the equations of chemical and meteorology model are solved by the same code and there is no need for a meteorological and pollution model. In addition, WRF/Chem includes a detailed urban canopy model (UCM) for modelling urban process in the first layers of the simulation. The WRF/Chem outputs are coupled with the Computational Fluid Dynamics (CFD) model called the MICROSYS running at high spatial resolution (meters). WRF/Chem with UCM (Masson 2000) model outputs at 1 km resolution was fed (offline) into MICROSYS to initialize simulations and to supply boundary conditions. The UCM sub-module simulates the principle of the town energy budget. The UCM model the turbulent flow within a canyon street using a resistance schedule and taking into account recirculation and ventilation of the air that influences turbulent heat flow within the canyon street. Shading modelling is done using sky view factors, which represent the area of the sky that allow urban structures to be seen as buildings from a specific point. The UCM is coupled to the WRF/Chem model and is run at each time step of atmospheric physics. The radiation exchange through the latent and sensitive heat fluxes calculated by the UCM is incorporated into the turbulent boundary layer scheme of the WRF meteorological model. Emissions are produced by EMIMO (UPM) (EMIssion Model) (San José et al., 2008) model for 2011. The core of the MICROSYS system is the MIMO CFD model, which models the effects of buildings on atmospheric flow. The model uses a three-dimensional grid where Reynolds equations are applied, a k-ε turbulence model is implemented and the 'advection-diffusion' equation is solved in order to simulate the transport of pollutants. In addition, a simple chemical mechanism for O3-NOx reactions has been implemented. Energy fluxes from and into surface have been implemented into The MICROSYS system also incorporates the UCM and NOAA (Land-Surface Model) schemes in the runs. In order to execute these models, it was necessary to develop a micro-shadow model, called SHAMO (UPM). It calculates the radiation with high spatial resolution (meters) taking into account the reflections that take place in urban environments. The simulations of the future have been run with current emissions (2011) because the objective is to isolate and quantify the specific impacts of global climate on the cities.

2.1.3 Health impact assessment

The health impact study calculates the percentages of mortality or hospital admissions related to changes in temperature or concentration of various atmospheric pollutants caused by global climate scenarios. These types of studies are based on data obtained from epidemiological studies that relate pollution and temperature data with health data about hospital admissions or deaths. As a result of epidemiological studies, exposure-response relationships are obtained that are applied to the results of climate projections and air quality modelling. In this study we have focused on short-term relationships between the number of deaths or hospital admissions by day and daily changes in exposure elements such as air temperature, heat waves events, ozone concentrations and particles of different sizes (PM10 or PM2.5). Different epidemiological studies have been published for different cities, all of them published in prestigious journals. Daily data on the estimated mortality or morbidity percentage per day for the different exposure variables selected: temperature, heat waves, ozone concentrations or particulates are averaged on a monthly and annual period for a more general overview of the health effects. Mortality and morbidity of some health effects or outcomes have been calculated: all causes of mortality, cardiovascular mortality, respiratory mortality, admission to respiratory hospitals and admission to cardiovascular hospitals. The effects are analyzed for the population of any age except in the case of heat waves where the associated mortality is for people over sixty-five years of age. The following climate-related exposure variables have been analyzed: Apparent Temperature (AT) and Heat Waves (HW), which are only considered for the summer months, from June to August. In order to establish the heat waves it is taken as descriptive variables: the maximum apparent temperature (ATMAX), to take into account the dirunal temperature and the minimum daily temperature (TMIN) that is usually reached at night. Concretely, a day of heat wave occurs when the ATMAX variable exceeded a threshold value or if the TMIN exceeded another threshold value. Each threshold is different for each city. In the case of air quality, I have taken as exposure variables the particulates (PM10) and tropospheric ozone. For the particles, we use daily averages and for the O3, we take a maximum of eight hours. The selection of the exposure variables and health effects studied is based on the availability of epidemiological data that provide the Relative Irrigation (RR) parameter, key to the calculations, as explained below. The relationship between the exposure variable and its effect on health is modelled through a log-linear (Poisson) regression named the exposure-response (ER) function. After, the last function is derivate, Equation 1 (Bell et al., 2006) is obtained, which has been implemented to calculate the change in mortality or hospital admissions due to a variation in the corresponding exposure variable.

$$\Delta y = y_0(e^{\beta\Delta C} - 1) \qquad (1)$$

where y_0 is the baseline incidence rate of the studied health effect, β define the mortality effect estimation which is published in the epidemiological studies, ΔC is the variation of the exposure variable (future - present). The results are expressed as a percentage change (%) in the health effect studied to make it independent of the exposed population and the incidence rate y_0. β parameter of the exposure-response function is defined by the Equation 2 (BenMap, 2010), it is calculated based on the relative risk (RR) associated with a given change in the exposure variable.

$$\beta = \frac{Ln(RR)}{\Delta c} \qquad (2)$$

In order to describe the health effect of exposure variables on mortality and morbidity, the following tables give the relative risk used in the health impact assessment and the reference where the values have been published. Table 1 for Milan and Table 2 for London.

Table 1: *Milan, relative risks values for each exposure variables and reference.*

Exposure Variable	Health Outcome	RR	LCL 95%	UCL 95%	Threshold	Reference
PM10 daily average	All causes mortality	1,003 74	1,0000 1	1,0074 9		Berti et al. 2013
PM10 daily average	Cardiovascular mortality	1,002 17	0,9958 3	1,0085 5		Berti et al. 2013
PM10 daily average	Respiratory mortality	1,005 38	0,9951 5	1,0157 3		Berti et al. 2013
PM10 daily average	Respiratory hospital admissions	1,004 41	1,0010 0	1,0078 3		Berti et al. 2013
PM10 daily average	Cardiovascular hospital admissions	1,003 99	0,9989 9	1,0090 1		Berti et al. 2013
O3 max mean 8h	All causes mortality	1,002 60	0,9987 0	1,0065 0		Allesandri et al. 2013
O3 max mean 8h	Cardiovascular mortality	1,002 40	0,9945 0	1,0103 0		Allesandri et al. 2013
O3 max mean 8h	Respiratory mortality	1,016 00	0,9875 0	1,0454 0		Allesandri et al. 2013
O3 max mean 8h	Respiratory hospital admissions	1,000 30	0,9956 0	1,0050 0		Scarinzi etl al. 2013
Apparent temperature max	All causes mortality	1,042 90	1,0335 0	1,0524 0	31,8 ºC	Baccini et al. 2009

Apparent temperature max	Cardiovascular mortality	1,037 00	1,0036 0	1,0704 0	31,8 ºC	Baccini et al. 2009
Apparent temperature max	Respiratory mortality	1,067 10	1,0243 0	1,1126 0	31,8 ºC	Baccini et al. 2009
Apparent temperature P90	Respiratory hospital admissions	1,022 00	1,0010 0	1,0440 0	33,8 ºC	Michelozzi et al. 2009
Days of heat waves	All causes mortality +65	1,336 00	1,2850 0	1,3900 0	Tmin>22,4 or Atmax > 36,2	D´Ippoliti et al. 2010
Days of heat waves	Cardiovascular mortality +65	1,392 00	1,3120 0	1,4760 0	Tmin>22,4 or Atmax > 36,2	D´Ippoliti et al. 2010
Days of heat waves	Respiratory mortality +65	1,925 00	1,7230 0	2,1510 0	Tmin>22,4 or Atmax > 36,2	D´Ippoliti et al. 2010

Table 2: *London, relative risks values for each exposure variables and reference.*

Exposure Variable	Health Outcome	RR	LCL 95%	UCL 95%	Threshold	Reference
PM10 daily average	All causes mortality	1,006 94	1,0034 9	1,0104 0		Katsouyanni et al., 2001
PM10 daily average	Cardiovascular mortality	1,005 51	0,9993 5	1,0117 1		Bremner et al. 1999
PM10 daily average	Respiratory mortality	1,002 86	0,9900 0	1,0100 0		Bremner et al. 1999
PM10 daily average	Respiratory hospital admissions	1,008 60	1,0049 0	1,0124 0		Atkinson et al. 2005
PM10 daily average	Cardiovascular hospital admissions	1,006 00	1,0030 0	1,0090 0		Atkinson et al. 2005
O3 max mean 8h	All causes mortality	1,003 10	1,0017 0	1,0052 0		Gryparis et al. 2004
O3 max mean 8h	Cardiovascular mortality	1,006 72	1,0009 7	1,0124 9		Bremner et al. 1999
O3 max mean 8h	Respiratory mortality	1,012 50	1,0046 0	1,0208 0		Atkinson et al. 2005
O3 max mean 8h	Respiratory hospital admissions	1,003 00	0,9945 0	1,0120 0		Anderson et al. 2004
Apparent temperature max	All causes mortality	1,015 40	1,0101 0	1,0208 0	23,9 ºC	Baccini et al. 2008
Apparent temperature max	Cardiovascular mortality	1,024 40	0,9991 0	1,0532 0	23,9 ºC	Baccini et al. 2008
Apparent temperature max	Respiratory mortality	1,061 00	1,0246 0	1,1108 0	23,9 ºC	Baccini et al. 2008
Apparent temperature P90	Respiratory hospital admissions	1,017 00	1,0070 0	1,0280 0	24,6 ºC	Michelozzi et al. 2009
Days of heat waves	All causes mortality +65	1,104 00	1,0860 0	1,1220 0	Tmin>16,8 or Atmax > 27,1	D´Ippoliti et al. 2010
Days of heat waves	Cardiovascular mortality +65	1,093 00	1,0660 0	1,1210 0	Tmin>16,8 or Atmax > 27,1	D´Ippoliti et al. 2010
Days of heat waves	Respiratory mortality +65	1,180 00	1,1340 0	1,2280 0	Tmin>16,8 or Atmax > 27,1	D´Ippoliti et al. 2010

3. Evaluation and results

To test the functioning and performance of the modelling system, one-year simulation for the present (2011) has been selected. This simulation is driven by the boundary conditions from the global reanalysis data (NNRP), which are the most realistic global data which represent the past atmospheric situation. NNRP data is used as boundary and initial conditions as well as global climate data. The modelled concentrations of various pollutants have been compared against the observational data available in the Milan, Kensington and Chelsea air quality networks. The evaluation has been carried out including the stations within the highest resolution (50 m) domains. A number identifies the monitoring stations. Number 0 station is a virtual station which represents the average value concentration of all stations. Some statistical estimators have been calculated in this study to analyse the performance of the air quality modelling system. These tools compare the observed values in the monitoring stations with the modelled values. By analysing the differences between the observed and modelled values we establish a combined systematic uncertainty (bias) and a random uncertainty (standard deviation). The root mean square error (RMSE) is also frequently used and it establish that if the RMSE value is small, the variance and the bias are also small. Additionally, the squared correlation coefficient (Pearson coefficient, R2) is defined as the established relation between modelled and observational data sets, providing a value between +1 and 0. This strong indicator establishes a linear relationship between these two variables. The value of +1 is showing a perfect linear relationship between observed and modelled variables and in case of 0, indicates that there is no relation at all between both data sets. Results are presented in the Table 3 for Milan and Table 4 for London.

Table 3: *Performance metrics for Milan*

STATION_ID	POLLUTANT	NMB (%)	RMSE (ug/m3)	R^2
5	SO_2	-5,27	3,6	0,21
0	NO_2	-0,01	38,07	0,51
0	CO	-0,05	574,4	0,67
0	O_3	-1,87	21,09	0,84
0	PM10	-0,24	30,95	0,58
0	C_6H_6	3,46	1,52	0,57

Table 4: *Performance metrics for London*

STATION_ID	POLLUTANT	NMB (%)	RMSE (ug/m3)	R^2
0	SO2	0,51	2,56	0,19
0	NO2	33,58	48,26	0,35
0	CO	17,73	136,87	0,37
0	PM10	34,87	18,39	0,46

Once the statistics corresponding to the comparisons between modelling results and data measured by the air quality stations have been obtained, we can conclude that the results are satisfactory and within the expected range according to the observed data. For the city of Milan we have obtained better results than for the city of London. This is because the information available for Milan modelling was more detailed; e. g. traffic flow data was available which is very important for estimating emissions at the microescala level. The modelled data follow the inter-annual variability of observed data, so that the R^2 values exceed the threshold of 0.5, except in some cases of SO2, although this pollutant currently tends to have low concentration values in cities. Evaluation statistics show significant evidence that the dynamic downscaling methodology applies is adequate and generates data that when compared with observations have acceptable quality as can be seen in BIAS and R2 statistics mainly. Now it is presented the most representative maps of the results for London (Figure 1 and Figure 3) and Milan (Figure 2 and Figure 4) taking into account the heat (Figure 1 and Figure 2) and air pollution (Figure 3 and Figure 4) effects on the citizen health.

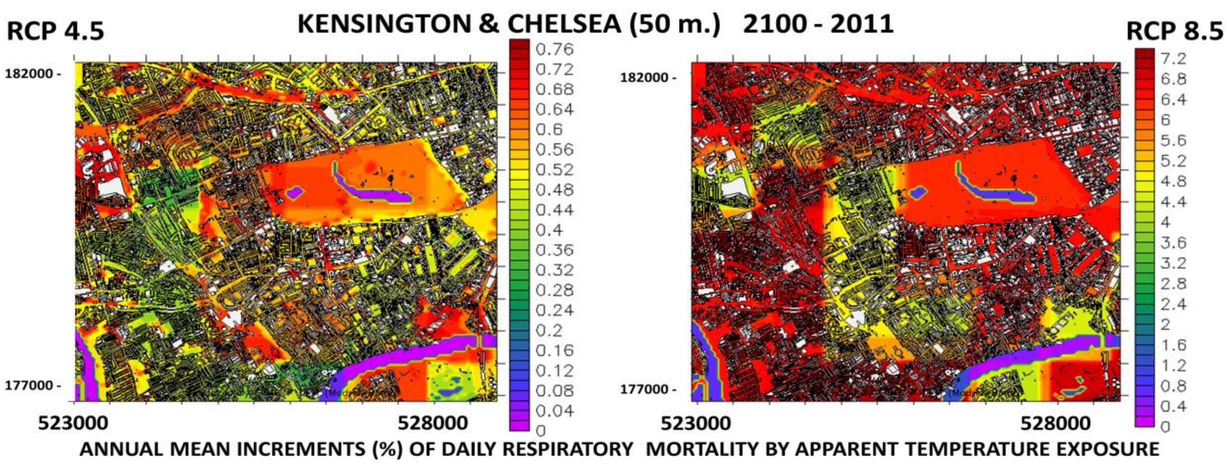

Figure 1: *Spatial distribution of the differences in annual mean change (%) respiratory mortality by apparent temperature for 2100 respect to 2011 following RCP 4.5 (left) and RCP 8.5 (right) scenarios with WRF-Chem-MICROSYS modeling system over London with 50 m. of spatial resolution.*

Figure 1 shows the relative increase in heat-related mortality by the end of the century. It is greater in the RCP 8.5 than in the RCP 4.5. We can observe a substantially lower mortality risk over the water bodies (purple areas). The average heat-related mortality percentage (around 7%) under the influence of a climate scenario such as RCP 8.5 is almost ten times higher than the expected rate for the climate scenario RCP4.5. These maps illustrate how health impacts associated with changes in global climate can increase further in the future if concentrations of greenhouse gases continue to increase as set out in the RCP 8.5 scenario or these effects can be stabilized if we manage to bring the future into a climate scenario defined as RCP 4.5.

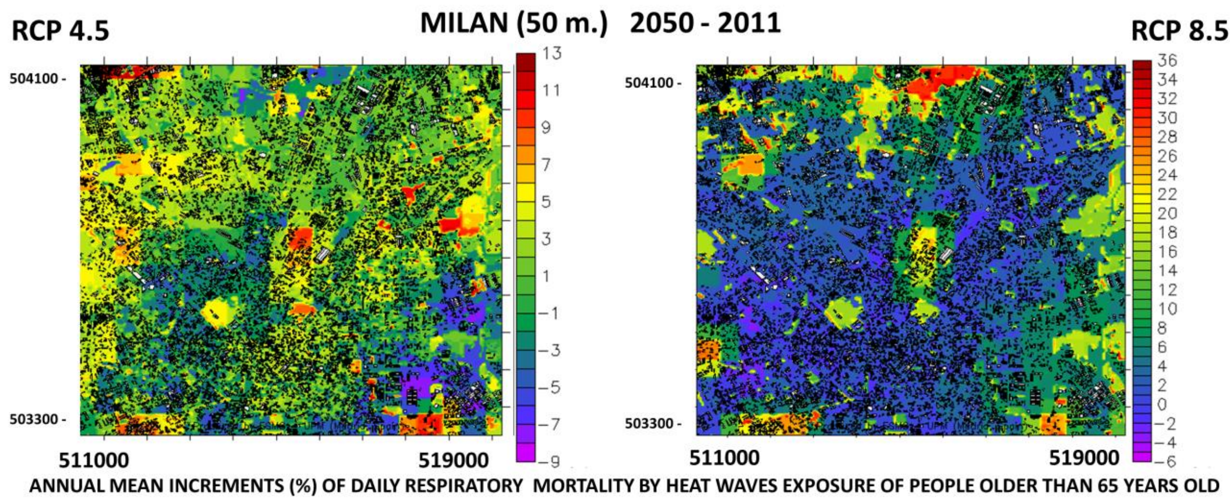

Figure 2: *Spatial distribution of the differences in annual mean change (%) respiratory mortality by heat waves for 2050 respect to 2011 following RCP 4.5 (left) and RCP 8.5 (right) scenarios with WRF-Chem-MICROSYS modeling system over Milan with 50 m. of spatial resolution.*

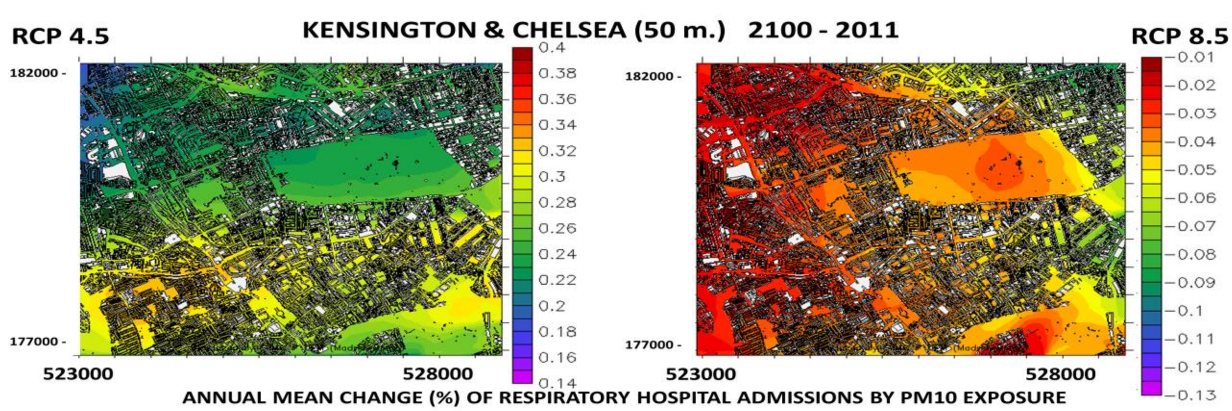

Figure 3: *Spatial distribution of the differences in annual mean change (%) respiratory hospital admissions (morbidity) for 2100 respect to 2011 following RCP 4.5 (left) and RCP 8.5 (right) scenarios with WRF-Chem-MICROSYS modeling system over London with 50 m. of spatial resolution.*

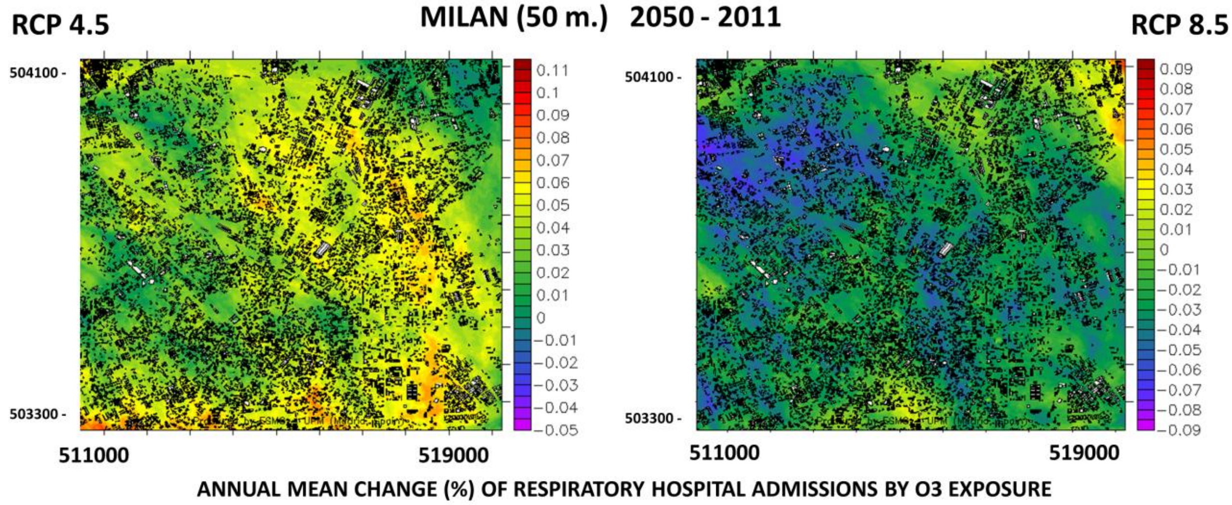

Figure 4: *Spatial distribution of the differences in annual mean change (%) respiratory hospital admissions (morbidity) for 2050 respect to 2011 following RCP 4.5 (left) and RCP 8.5 (right) scenarios with WRF-Chem-MICROSYS modeling system over Milan with 50 m. of spatial resolution.*

Figure 2 shows the annual mean respiratory mortality caused by heat waves for year 2030 compared to baseline year 2011 for both scenarios RCP 4.5 and RCP 8.5. The impact of the RCP 8.5 is very important with areas, located at North of city of Milan, close to the 30% of increment for people older than 65 years old. As in London case mortality rates will greater in the RCP 8.5 than in the RCP 4.5. In small areas with the RCP 4.5 the citizen health of people could be improved thank you to reduce the temperature increases. Figure 3 (London) we can see largest climate change-drive relative increase in PM10-related hospital admissions to have occurred in the RCP 4.5, an increase of up to 0.4 % is estimated. A decrease is estimated for the RCP 8.5 with the largest decrease, by -0.13%. In the Figure.4 (Milan) the global climate estimates impacts using RCP 4.5 and RCP 8.5 do no vary greatly. The relative increase of respiratory hospital admissions in some areas of the south and east of the Milan domain are expected to be close to 0.1 with the RCP 4.5 and very small changes are expected with the RCP 8.5.

4. Conclusions

In this work, an integrated modeling framework has been presented to quantitatively analyze the possible impacts of climate scenarios on citizens' health, using a high special and temporal resolution. In addition, examples and results of the application of the tool for two cities have been shown. The integrated framework predicts future projections of climate and air quality and their effects on citizens' health with a spatial and temporal resolution appropriate for urban planners. The system has been developed in a modular way, giving it flexibility and adaptability that allows it to be used in any city of the world. Results of an assessment of the potential impacts of climate change on mortality and morbidity in two largest cities Milan and London have been presented. These results have been got from outputs from a climate model with two Representative Concentration Pathways, RCP 4.5 and RCP 8.5 set up by the Intergovernmental Panel on Climate Change (IPCC)'s Fifth Assessment Report.

The evaluation results have indicated that the air pollution simulation performed very well in reproducing historical hourly air pollution concentrations using downscaled global climate model outputs. Milan experienced a higher heat effect at very high temperatures compared to London. The highest increase of mortality was found in the worst scenario (RCP8.5), these increments will be more obvious from the 2050s to 2100s. The selection of the RCP climate scenarios is very important in projecting future heat-related mortality, particularly in the second half of the century. The results indicate the potential large effect climate change could have on future heat/air quality-related mortality and morbidity over urban areas. The health effects are based on meteorological data and the air pollution concentrations produce by the dynamical downscaling models. These datasets have a uncertainty related to the uncertainty of the numerical models and input data which has been estimated in the evaluation process. This uncertainty can be reduced running different models and build an ensemble mean which will perform better than individual members. There is also uncertainty on the expose-response relationships (Benmarhina en atl., 2014). Future studies may consider applying different concentration-response coefficients. The results of our study can help to stakeholders interested in developing strategies to mitigate the effects of the global climate on the citizens and building resilience urban areas.

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