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Article

An agent-based modeling framework for simulating human exposure to environmental stresses in urban areas

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Abstract: The importance of predicting the exposure to environmental hazards is highlighted by issues like global climate change, public health problems caused by environment stresses, and property damages and depreciations. Several approaches have been used to assess potential exposure and achieve optimal results under various conditions, for example, for different scales, groups of people, or certain points in time. Micro-simulation tools are becoming increasingly important in human exposure assessment, where each person is simulated individually and continuously. This paper describes an agent-based model (ABM) framework that can dynamically simulate human exposure levels, along with their daily activities, in urban areas that are characterized by environmental stresses such as air pollution and heat stress. Within the framework, decision making processes can be included for each individual based on rule-based behavior to achieve goals under changing environmental conditions. The ideas described in this paper are implemented in a free and open source NetLogo platform. A simplified modeling scenario of the ABM framework in Hamburg, Germany, further demonstrates its utility in various urban environments and individual activity patterns, and portability to other models, programs and frameworks. The prototype model can potentially be extended to support environmental incidence management by exploring the daily routines of different groups of citizens and compare the effectiveness of different strategies. Further research is needed to fully develop an operational version of the model.

Keywords: environmental stress; human exposure; agent-based model; air pollution; urban heat wave; exposure modeling; climate change

1. Introduction

1.1 Human exposure to environmental stresses

Human health is closely related to the surrounding environment. People are exposed to a variety of factors that can be hazardous to health, including the physical living environment. A series of climate change-related risk factors (rising sea levels and storm surges, heat waves and droughts, typhoons and extreme precipitation, inland and coastal floods) have been and will continue to pose serious risks to human society [1]. The strength and frequency of many risk factors tends to increase. The occurrence of these hazards often stresses human health and welfare, e.g. through diseases, property damage, economic loss and ecological environment degradation. For instance, extreme

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rainfall causes urban flooding which often leads to large economic losses and serious threats to urban safety [2] while heat waves are harmful to public health, especially to vulnerable groups, which is the most significant reason of weather-related deaths [3]; the effects of air pollution, drought, wind, snow and freezing weather on the normal operation of the city are also becoming increasingly prominent [4].

Over the last decade the combined effects of a set of environmental factors on health concerns have received growing attention in research and rising awareness of the risks posed by heat waves, air pollution, noise, visual and social loads, and similar phenomena [5-7]. Most studies have focused on the effects of one or two of these environmental stressors and found significant effects on health risk.

1.2 Human health in urban environments

Cities are a highly artificial environment, quite special and different from the natural environment that humans have always been living with. Urban environments can be highly stressful, where humans are exposed to multiple sources of environmental discomfort, such as air pollution, high temperature, noise, odor and social burdens [8]. As a result the health and wellbeing of humans can be negatively affected by the urban environment [9]. Humans in cities often cannot avoid being exposed to stressors, as they must work, shop, travel, or entertain in the cities. Working or staying for a long time outside is the main way of being exposed to a stressful environment, followed by travelling, particularly walking and cycling [10]. Even staying indoors, people are exposed to risks of high temperature, noise and air pollution, of which the effects often can penetrate into buildings.

The overlap of global climate change and urbanization makes cities the places where risks are concentrated and intensified due to the high density of population, building, traffic and other urban infrastructures [6,11]. Modern cities can improve health via the provision of services as well as material, cultural and aesthetic attributes. They also offer opportunities for cost-effective interventions that can serve many people. Urbanization represents both opportunity and risk, and offers a fresh set of challenges for those concerned with protecting and promoting human health and wellbeing. However, environmental hazards remain and new threats have emerged [12]. Urban air pollution - of which a significant proportion is generated by vehicles, as well as industry and energy production - is estimated to kill some 2 million people annually [13]. Such stresses can worsen in the future, considering that more than half of the Earth's population currently lives in cities (54% by 2014), and by 2050 this proportion will rise up to 66% [14].

Over the next thirty years, most of the world's population growth will occur in cities and towns of developing countries, mainly in Africa and Asia [14]. As urban populations grow, the quality of the urban environment will play an increasingly important role in public health with respect to issues ranging from solid waste disposal, provision of safe water, sanitation and injury prevention, to the interface between urban poverty, environment and health [15].

1.3 Dynamics of environment exposure

Since humans are an active component of cities, human exposure to the urban environment is strongly linked to the various processes inherent in human mobility, to the distinctly local and individual characteristics (e.g. clothing type, travelling tool, physical quality) and finally to the quality of the natural, built and social environment [9,16]. While people move, the environment in which they are located and their exposure to the environment changes dynamically. In addition, available evidence indicates that personal exposure to many pollutants is not adequately characterized because the time people spend in different locations and their activities vary dramatically with age, gender, occupation, and socioeconomic status [17,18]. Thus, the exposure is dynamic, and the challenge for research is to analyze the complex relationships between individual and its local environment, to explore new exposure mechanisms under mobility, to identify universal and specific local conditions in the urban context [19].

Preventing and reducing harmful exposure requires understanding of exposure dynamics, in particular its sources, intensity, extension, duration, process and impacts [20]. Different microenvironments (e.g., temperature, humidity, shadow, wind) and activities (e.g. working, shopping, and entertaining) lead to everyday exposure levels of people moving in the city. Yet, if the threats can be so different, they could affect the same people. The challenge is thus to find innovative, efficient approaches to collect, organize, store and communicate exposure data on an individual level, while also accounting for the inherent spatial-temporal dynamics.

Models are appropriate tools to reach understanding on this issue. A dynamic individual exposure model is able to evolve as the individual moves would lay the basis for an assessment of the exposure level by providing reliable and standardized information on the exposed objects across a vast range of human activities [21]. In this paper, we explore the different types of exposure models in the urban environment, their characters and advantages, and define both their spatial and socioeconomic dimensions. By identifying research gaps in recent exposure models, we emphasize the capacity of agent-based model to fill the gaps and present an agent-based model prototype to integrate the dynamic and individual features of human exposure in urban environments. The aim of the paper is to assess the challenge of implementing a dynamic exposure model for individuals of different but specific mobility within an agent-based modelling framework.

2. Modeling approaches for assessing environment exposures

A wide variety of exposure models are employed for assessments of human exposure to environment stresses. These existing exposure models can be broadly categorized according to their target objects: modeling of exposure sources, exposed objects (receptors), and of accumulated exposure consequences (integrated in Table 1). In this section each of these basic types of exposure model are briefly described, along with inherent strengths or weaknesses, following with an analysis of the gaps and capacities of an agent-based model.

2.1 Modeling of exposure sources

The modelling techniques adopted in current exposure models have evolved along distinct lines for the various types of source [22]. An elementary step towards a modelling assessment of the exposure to new compounds or pollutants (chemicals, materials) is to estimate their environmental concentrations [23]. Most of these studies focusing on the concentrations of environmental risk factors use mathematical models based on measurements extracted from a small number of fixed climatic monitoring stations within indoor and outdoor urban types of environments [24]. Jerrett, *et al.* [25] reviewed these models and sub-classified them as (i) proximity models, (ii) interpolation models, (iii) land use regression models, (iv) dispersion models, and (v) integrated emission-meteorological models. Geographical Information Systems (GIS) are often applied in these models to demonstrate spatial and temporal patterns of environmental pollutants. Nevertheless, these kinds of models aim to extrapolate the concentration distribution of the environmental stressors considering various factors that affect patterns of distribution in the research area, mostly (part of) a city [26, and others in Table 1].

Schnell, Potchter, Yaakov and Epstein [24] criticized such models: 1) they underestimate concentrations of risk factors using limited monitoring measurements; 2) the complexity of pollutant distribution patterns was hardly accurate in these models; and 3) the indoor environment was ignored when using only outdoor monitoring data. Beyond Schnell's criticism, these models mostly focus on a single stressor of concern and describe a few pathways through which the receptor, either a human or another organism, can be exposed [27]. However, awareness is growing that exposure to single stressors is the exception rather than the rule [28]. In practice, organisms are often exposed to multiple stressors, e.g., extreme weather, a chemical mixture or a combination of chemical, biological and physical agents. Exposure to multiple stressors may take place concurrently or sequentially, and the individual stressors may or may not interact [28].

To some extent, the effect of stressor concentrations cannot really be represented by exposure models if there is no specified subject that suffers from the stressors. Moreover, due to raising concerns of people-centered urban management, to date, the monitoring of urban environments has not taken into account the dynamism of urban daily life [19]. Humans in the city are actively mobile

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which influence greatly the consequence of individual exposures. Therefore, current studies intend to combine the modeling of exposure sources with human and/or other exposed subjects [20,29].

Table 1. Selected sample models in studying human exposure to environmental stressors

Category	Model principles	Example models/applications	Representative References	Model features
Modeling of exposure sources	Estimation of the concentration, distribution and transportation of exposure sources (pollutants, heat, humidity, radiations, etc.)	- Global air pollution (fine particles & ozone) assessment - Atmospheric Dispersion Modelling System (ADMS 5) - Land use regression (LUR) models - Multimedia Exposure Assessment Modeling - Water quality regression model - Indicator based heat and air pollution combination - Scenario projections from regional climate models	[26] [30] [31] [29] [32] [20] [33]	- Mainly physical aspects of exposure sources - Receptors ignored - Suitable in large scale and outdoor exposure - Result is a map (map set) of stressor concentration
Modeling or assessment of exposed population	- Assess the population or area or property that is exposed to certain stressor concentrations - compare the exposure status/level of sub-regions or sub-group of population	- Modeling exposure to natural hazards like flooding, cyclone, droughts - Global and regional human exposures to air pollutions - Noise exposure model - Traffic noise and pollution exposure model - heat stress exposure model in combination with traffic model	[34] [35] [36] [37] [38] [39] [40]	- Offer an overview of group exposure - Produce relative comparison of sub-group's exposures - Suitable in large scale and outdoor exposure - Result is a population or area associated with certain stressor concentration (population-weighted concentrations)
Modeling of individual's exposure degree	- Assess the accumulation of exposure at a series of time and locations - Simulate the exposure degree of specific receptors - Mostly adopted with receptors' mobility and activity	- CARES (Cumulative and Aggregate Risk Evaluation System) - Lifeline (exposure to pesticide) - Mobile-tracked traffic-related air pollution model - Urban exposure in daily life routines - GPS-based modelling of urban exposure to air pollution - Modeling exposure to multi-stressors - Personalized model of pesticide use	[41] [42] [43] [24] [10] [7] [44] [45]	- Focus on sampled individual receptors - Suitable to model multiple stressors - Limited number of receptors - Specific and accurate at individual level - Result is an integrative degree/intensity of a subject being exposed (time-weighted concentrations)

2.2 Modeling of population exposure

Models of population exposure go a step further than the stressor concentration models do. These models generally assess the size of a population, the area and/or property that is exposed to certain stressor concentrations, and may also compare the exposure level of sub-regions or sub-groups (Table 1). Natural hazards like flooding, sea level rise, snow avalanches, droughts are among the mostly targeted exposure sources. For example, the nation-wide exposure assessment in Austria covers river flooding, torrential flooding, and snow avalanches [35]. A mapping study of flood

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exposure detected flood inundation areas and the affected people [46], which indicated that exposure depends strongly on the temporal and spatial dynamics of the distributed population. A few studies also estimated global exposure to floods and revealed the economic exposure, population exposure and geographical distribution of regional exposures [34,47,48]. Overall, these modeling approaches help identifying highly exposed regions and are an important and suitable tool to inform regional or nation-wide adaptation. Also the impact of the structure and morphology of cities on heat stress exposure of urban commuters has been investigated by combining a simple heat stress model with a traffic model that can track certain groups of commuters [40].

Population exposure models have been widely applied to explore human exposure to air pollutions. Hystad, Setton, Cervantes, Poplawski, Deschenes, Brauer, van Donkelaar, Lamsal, Martin, Jerrett and Demers [36] created national pollutant models to produce estimates of population exposure to five common air pollutants (PM2.5, NO2, benzene, ethylbenzene, and butadiene) in Canada. Global and regional exposure to black carbon [37], metals [49] and ozone [26] were also estimated using similar approaches. Besides, a noise exposure model for London indicated that over 1 million residents were exposed to high daytime and night-time noise levels [38]. Modeling of traffic pollution exposure in Toronto revealed the highest polluted areas and periods along roadways at peak levels of traffic but the highest population exposure in the central business district due to the higher population density [39].

Population exposure models often place strong emphasis on the geographical distribution of populations, stressors and their estimated level or intensity of exposure, which might be called population-weighted stressor concentrations [37]. These models have advantages in identifying geographic areas, usually larger than a city, where hotspot exposures are a potential risk to human health, and are informing decision making to reduce exposure inequalities [49]. New developments in sensor technology now enable us to monitor multiple stressors and personal exposures in activity spaces and fields of varying concentration [16].

2.3 Modeling of individual's exposure degree

Individual exposure models simulate the exposure level of each receptor based on their individual characteristics and within a pre-set specific route and/or space (Table 1). These approaches were often seen in mobility-related exposure studies using empirical or experimental traffic data for specific individuals **[43,50]**. Leyk, et al. (2009), presenting a spatial individual-based model prototype for assessing potential pesticide exposure of farm-workers with their individual level track of movement and activities. Similarly, more complex modeling tools were developed for quantification of human exposure to traffic-related air pollution within distinct micro-environments by using GPS trajectory analysis of the individuals in the city area [10,24]. Findings of these approaches show the exposure of people to environmental sources of discomfort while performing their daily life activities [7,10]. These studies suggested a shift from measuring environmental conditions in fixed monitoring stations to monitoring with mobile portable sensors [44,51].

Individual exposure models were applied in both human models and wildlife models. Loos, Schipper, Schlink, Strebel and Ragas [28] compared five human and five wildlife receptor-oriented exposure models and identified their similarities regarding exposure endpoints, chemical stressors and the extent of model validation, as well as the differences relate to the simulation of behavior and the representation of individuals and space. In addition, an individual receptor can be considered as an integrator of different stressors to which it is exposed while moving through space and time. Therefore, exposure models for multiple stressors should primarily focus on the receptor, and not on the stressor(s). A few studies have indeed reported the applicability of individual-oriented models in modeling noise, black carbon, particle number concentrations, and multiple chemicals [41,44].

The assessment of individual exposure often aims to tell the total exposure degree or intensity with a process of moving in different space sites. Sampling approaches are generally applied to collect exposure data at different location and time, often along a planned routine in a city. The assessment shows the consequence of accumulated exposure degree that is often a function of the stressor concentration and the duration of being exposed, or so called time-weighted concentrations [52]. As

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indicated in table 2, most individual exposure models don't consider human exposure as a dynamic process but as a summary over several time points/periods. This may be discussable in case of long time continuing environment threats, for example, a heat wave that lasts several days. In practice, monitoring of individual exposure is limited to studies with a small number of individuals because of the high costs and complex organization associated with the measurements [10,51]. The results are very much accurate and reliable at personal level, though they don't show a big picture of the exposure pattern of the whole city or area.

2.4 Research gaps and capacities of agent-based modelling

As shown above, dozens of studies have measured the concentrations of numerous stress sources in different media to which humans are exposed. Others have catalogued the various exposure pathways and identified the duration and accumulation of exposure for the general population. All of this information allows better estimates of exposure. However, literature reviews have demonstrated that the role of individual mobility for exposure was less explored and based on limited monitoring data of personal samples [19]. The relationship between individual heterogeneity and uniform group patterns, especially for peak exposure in "hot-spots" is still insufficiently addressed and the contribution of mobility-related exposure is not clear [7]. In addition, the dynamic process of changing exposure to various individuals requires innovative models that can identify the emerging non-linear patterns of collective exposures. We hypothesize that a computer simulation tool with a large number of individual random activities in different types of environments can provide a better understanding of the consequences of human exposure to environmental risk factors throughout the concerned space and time range.

To fill the research gaps and test the hypothesis, we recommend the development of an overall framework for exploring the spatial and temporal variability of individual exposure concentrations and emerging collective exposure patterns, a screening tool for exposure source concentrations, the collection of better source and receptor data, the demonstration of exposure processes and collective exposure patterns. While a few researchers have mentioned similar ideas taking into account activity spaces and daily mobility in measuring environmental exposures [7,19,53], the present study is a practical effort to implement them. An agent-based model (ABM) is a suitable tool to implement such dynamic non-linear and collective simulations, as reviewed in existing studies on coupled human-nature systems [54].

An agent-based model considers the essential known and measurable aspects of an agent and acknowledges the nonlinearities and underlying dynamic processes [54-57]. An agent-based approach can make an important contribution to improving health and wellbeing, both at individual and collective group levels. In an ABM, agents are described by self-contained computer programs that interact with its environment and with one another and can be designed and implemented to describe rule-based behaviors and modes of interaction of observed social entities [55,58,59].

Regarding the field of environmental exposure studies, ABMs have the advantage to simulate the exposure consequences of individual activities and the patterns of collective group exposures, thus to suggest exposure reduction strategies accordingly. Currently, there is limited understanding of the complex mobility exposure to environmental stresses in the specific urban context. There is an urgent need to develop an innovative and operational approach to understanding urban health and wellbeing that integrates individual characters within a mobility context. This, in turn, will help to integrate substantive consideration of individual wellbeing into long-term planning, development and management of urban environments. Exposure estimates to atmospheric pollutants can address individuals (personal exposure) or large population groups (population exposure) and can be based on direct (exposure monitoring) or indirect methods (exposure modelling). Efforts aiming at providing useful global models have given rise to freely available, web-based databases, each acting as a collector of the different data and models representing geophysical and meteorological risks.

3 An agent-based modelling framework

An agent-based prototype model to urban environment stresses is developed in the present work for quantification of human exposure within distinct microenvironments and a novel approach based on daily routine analysis of individuals. Subsequent sections provide the context on the model environment and its implications for health, and outline a conceptual framework for the study of health and wellbeing in and between urban spaces. Finally, guidance on research criteria and the use of a systems approach is offered to prospective investigators for the development of research proposals.

3.1 Model structure

The model framework is structured in three overlapping layers: spatial data of the concerned urban environment, concentrations of environmental stress sources, and human activities. Figure 1 illustrates the ABM used in this paper.

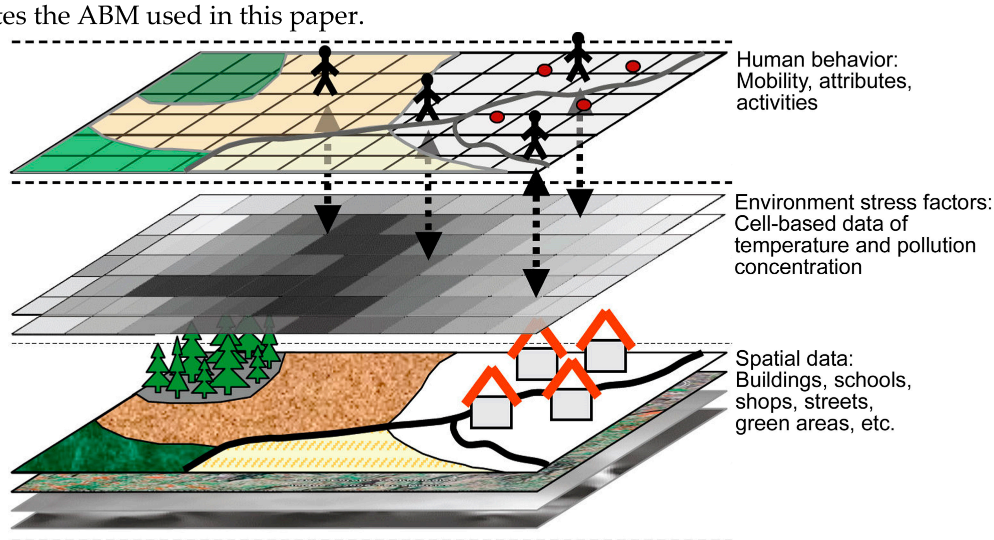

Figure 1. Illustration of the agent-based model framework for environmental exposure simulation. Applied and illustrated based on Leyk, Binder and Nuckols [45]

In this framework, spatial data of the changing concentration patterns of the environmental stress factors are the key pre-set inputs that build up the natural aspects of the system (center layer in Figure 1). A specific map will be used to represent the city with buildings, streets, shops, green areas, etc. (lower layer in Figure 1). Agents with initiated attributes act daily to work, rest, entertain, shop, take care of children, and follow certain paths to work (top layer in Figure 1). Once the prototype model is initialized, agents act on their daily life according to predetermined rules that are set according to empirical studies and specific surveys. Depending on their normal lifestyles (different among agents) as well as the environment stress factors of their location, they suffer or reduce exposure levels. A simulation during a heat wave or air pollution event, with a period from hours to days, would report a cumulative exposure level for each agent and a collective pattern of all agents in the study area. The loops of agents' daily activities and the evolution of the stressful factors drive the model to run step by step, so that the exposure process can be analyzed. Finally, the model produces summary information that can be used to diagnose both individual and collective exposure and inform relevant exposure reduction strategies. Further details of the model components are introduced in the following sections.

3.2 Modeling environment

The modeling environment includes two parts, the natural environment of the studied city area and the stressed environment of a heat wave or air pollution event. The natural environment of the city is represented by an integrated computable map of land-use data, street and building information, key sites, and so on. Such data are usually available in GIS format.

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In addition to data from the urban environment, geospatial data for the stressed environment are needed to map the impact on agent movements. Environmental stressors such as high temperatures or air pollution can be taken from measurements or from atmospheric model simulations. These are usually gridded datasets with a fixed spatial resolution. The temporal resolution typically varies between minutes and several hours. For simulating the exposure to stressors both high spatial and temporal resolutions are desired. However, there are limits set by the availability of observations, by the resolution of the models or the computing resources (e.g. disk space, working memory or computing time).

The introduced modelling framework aims to simulate the exposure to air pollution and heat stress in an urban area. Air pollution is elevated in urban areas mainly due to emissions from traffic (fossil fuel driven vehicles and ships), industry and residential heating. Therefore, high concentrations can be expected near big roads, harbor and industry areas. Pollutants range from larger particles such as particular matter (PM) to gases such as Ozone, NOx, CO, etc. Most of them are formed after several chemical reactions. Hence, chemistry models are applied to simulate the concentration levels within urban areas [60]. The emissions of chemicals, which are crucial for the chemistry model, are usually estimated from traffic, census, and monitoring stations.

It is well known that due to the heterorganic surfaces and three-dimensional structures (e.g. buildings, trees, bridges etc.) temperatures and heat stresses can vary strongly within a city [61]. At night-time the so called urban heat island (UHI) can develop for low wind speed and cloud cover [62]. The UHI refers to higher near-surface temperatures in urban areas compared to the rural surroundings. Also during the day temperatures are varying within the city. Especially, green and blue areas (e.g. parks, lakes, rivers, etc.) have a cooling effect during the day. Since humans do feel the environment as a combination of the meteorological variables temperature, humidity, wind speed and long- and shortwave radiation, rather than temperature alone so-called biometeorological indices are computed, which summarize the combined effect of the thermal environment on the human heat budget of a person [63]. The developed prototype uses artificial temperature data randomly chosen from a typical temperature range for Hamburg to validate the model because high-resolution daily or hourly temperature or heat stress data for Hamburg are only available for periods with a length of 3-4 days in summer [64,65].

3.3 Agent attributes and behaviors

The urban population is quite diverse, consisting of people of different ages, gender, living and working location, social background, lifestyles etc. Hence, they all show a unique behavior. Modelling each urban dweller of a city like Hamburg with 1.7 million citizens is not feasible due to computing constraints and more importantly due to the lack of available data. However, it is possible to group people with similar attributes and behaviors to agent types based on surveys, traffic data and data from public transport companies. The behavior of urban dwellers can depend on age, gender, work, income, education, living and work location, access to cars or public transport, and environmental conditions (e.g. rain, temperature, and pollution levels). Crowd-sourcing information on detailed time-location data can also be collected for each individual at each moment by GPS-equipped mobile phones, offering many advantages over traditional time-location analysis, such as high temporal resolution and minimum reporting burden for participants.

3.4 Daily routines

As mentioned before, agents have goals that they are following. These could be to go to work every day, to take children to school or day care, etc. To facilitate the modeling, it is hypothesized that the daily routine of a certain group of agents is uniform. This makes it possible to simulate as many agent types as determined in grouping processes. According to the grouping properties of the agents, the empirical data and survey data are used to generate synthetic daily routines, with agent priorities for each option of the population commuting between different directions. To capture variability in the travel survey and uncertainties in behavior, the synthetic daily routines can be described as action probabilities or priorities p. An example of a synthetic daily routine for a female agent, employed and aged 30-45 with one child is shown in Figure 2. In this example, the agent starts the day at 8 am with standard deviation of 15 min. They then travel, via school to drop their children off, to work with a 0.2 probability of visiting the shops for a while on route and so on. Parts of this daily routine can be different among agents of the group, e.g. the staying time in a shop, but agents in this group all have to visit such many places on the route.

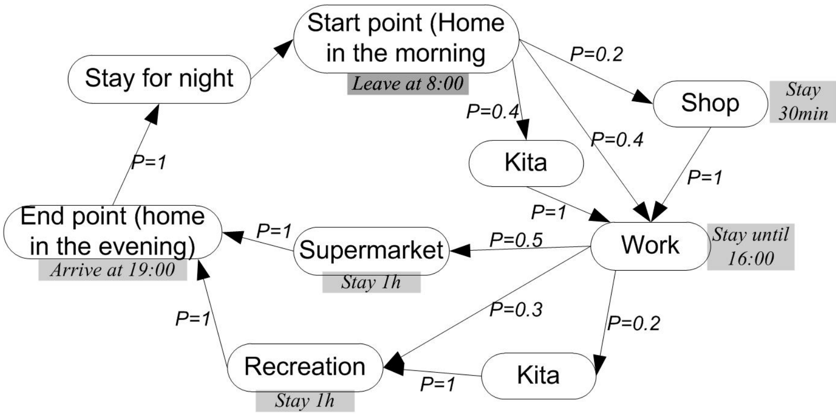

Figure 2. Example of a daily routine for a female agent, employed, aged 30-45 with one child

4 Model implementation and results

In order to demonstrate the applicability of the ABM framework a prototype model implemented in the Netlogo platform is set-up for the city of Hamburg which simulates the exposure to air pollution of different kinds of agents living near the city center during their commute to work (Figure 3). A detailed description is given in Rühe [66]. In the following, the employed data (Section 4.1), the agent types (Section 4.2), and the model formulation (Section 4.3) are described briefly. In addition, some first results are presented (Section 4.4).

Figure 3. Map of commuting routes from home location (red house on the right) to work location (big red house in top left corner) implemented in NetLogo. The third small house represents day nursery. Each note represents a point where the exposure is calculated new. On each intersection agents decide which path they

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use. The different colors represent the means of transport (blue=car, green=bike, yellow=public transport). For car and bike different routes are possible indicated by the different shades of blue and green.

4.1 Data preparation for the case city of Hamburg

In the present model, NO_2 concentration data are taken from model results from chemistry transport model CityChem (Ramacher et al., 2017). The data are averaged for the summer and winter of 2012 on a 250 m × 250 m grid. Values for temperature are taken from the DWD (German Meteorological Service) and are randomly set at the same grid using typical ranges for summer (17 – 24.9 °C) and winter (0 – 8.9 °C). As soon as long-term high-resolution temperature or heat stress data are available, they can be implemented with the same input routine used for the $N0_2$ data. For simplicity the routes as well as the home and work locations are predefined (Figure 3 and Table 2). Information about the costs for taking the car were taken from ADAC (Allgemeine Deutsche Automobil-Club), information about bike costs from the Federal Environment Agency (Umweltbundesamt) and the costs for public transportation in Hamburg were taken from the public transportation service of Hamburg, HVV homepage (www.hvv.de). With this information it is possible to calculate overall costs for each path.

Table 2. Time, length and costs for the different routes.

	Car1	Car2	Car3	Car4	Car5	Bike	Public
Time [min]	10	16	17	15	13	19	18
Length [km]	5.1	5.3	6.8	7.1	6.6	5.0	6.3
Costs [€]	1.53	1.59	2.04	2.13	1.98	0.4	1.07

4.2 Settings of agents

The agent types are characterized by their different initial priorities for car, bike and public transport ($p1$, $p2$, and $p3$), their different weights for costs, time, temperature deviation, exposure (α, β, and γ), adaptation rate A and desired temperature $T_{desired}$ (Table 3). The values are set for typical urban dwellers. Therefore, artificial values are used to create meaningful citizens. This work tries to represent a broader cross section of society. This is why agent types reach from college students with small amounts of money available, with high weights for costs and a high priority for bike transportation, to old retired people with low weights for costs and with high priority for car transportation.

Table 3. Attributes of different agents.

Agent type:	Alfred	Bob	Chris	Dean	Earl	Frank	George
prioritycar	0.1	0.95	0.65	0.333	0.1	0.333	0.8
prioritybike	0.7	0.025	0.001	0.333	0.2	0.333	0.1
prioritypublic	0.2	0.025	0.3499	0.333	0.7	0.333	0.1
A	10	0.1	1.2	3	0.1	4	2
α	0.6	0.05	0.3	0.1	0.45	0.8	0.8
β	0.1	0.75	0.1	0.7	0.45	0.1	0.1
γ	0.3	0.2	0.6	0.2	0.1	0.1	0.1
Temperatureaim [°C]	23	18	21	23	23	19	28

4.3 Model formulation

In the model, agents are commuting to work using different means of transport (i.e. car, bike and public transport) as well as different routes, where they are exposed to different air pollution and temperature levels. The decision on which mean of transport to use is based on the priority p for the k different choices while the change of the priorities is based on a value function v which in our case is the weighted sum of commuting costs c_c, commuting time c_t, deviation from a desired temperature d_t (|T-T$_{desired}$|) and the accumulated exposure to NO_2 e_{NO2} (Eq. 1). An exposure to NO_2 occurs if a threshold of 30 µg/m³ is reached.

$$v_{i,k} \leq 0$$

$$v_{i,k} = -\left(\alpha_i\left(\frac{c_{ck}-c_{cmin}}{c_{cmax}-c_{cmin}}\right)+\beta_i\left(\frac{c_{tk}-c_{tmin}}{c_{tmax}-c_{tmin}}\right)\right)+\gamma_i\left(\left(\frac{d_{tk}}{d_{tmax}-d_{tmin}}\right)+\left(\frac{e_{NO2k}-e_{NO2min}}{e_{NO2max}-e_{NO2min}}\right)\right) \quad (1)$$

The parameter α, β, and γ represents the relevance of each term, which can differ between the agents. The sum of all three parameters is 1. In order to make the different terms comparable they are normalized with respect to their maximum and minimum. Hence, values can range from 0 to 1. For simplicity the normalized exposure to high/low temperatures and the exposure to NO_2 are combined into one exposure term in the current version of the model. This means that they are currently equally weighted because it is not yet clear how to combine the effect of exposure to both stressors on the health of the agents.

Following Scheffran and BenDor [67] the change in priority is computed using Eq. (2).

$$\Delta p_{i,k} = a_i \cdot p_{i,k}\left(\frac{v_{i,k}-\sum_{l=1;l\neq k}^{n} v_{i,l} \cdot p_{i,l}}{\sum_{l=1;l\neq k}^{n} v_{i,l}}\right) \quad (2)$$

where a_i is the adaption parameter of agent i representing how fast an agent adapts and reacts to changes. After each time step new priorities are computed (Eq. 3).

$$p_{i,k}(t) = p_{i,k}(t-1) + \Delta p_{i,k}(t-1) \quad (3)$$

The values for the exposure are computed during the model run while the values for costs and the commuting time are currently predefined.

4.4 Preliminary results

In the developed model several model runs were conducted starting with model validation runs, where "extreme" agents (e.g. setting α=1, β=0, and γ=0) are used to test for consistency and plausibility. Afterwards, runs under simple conditions for all agents is executed followed by one runs with low costs for public transportation, runs where rain is turned on, where a construction is blocking one road and runs where the effect of NO_2 in summer and winter is analyzed. The prototype model is integrated for 120 days keeping the environmental conditions. It is obvious that a rain event strongly affects the agents with a high *priority$_{bike}$*. Once a switch to public transport occurs (Figure 4), this has a negative effect on the agents' capital because costs for public transport are much higher than for bike. Agents with highest priority for cars are not affected at all.

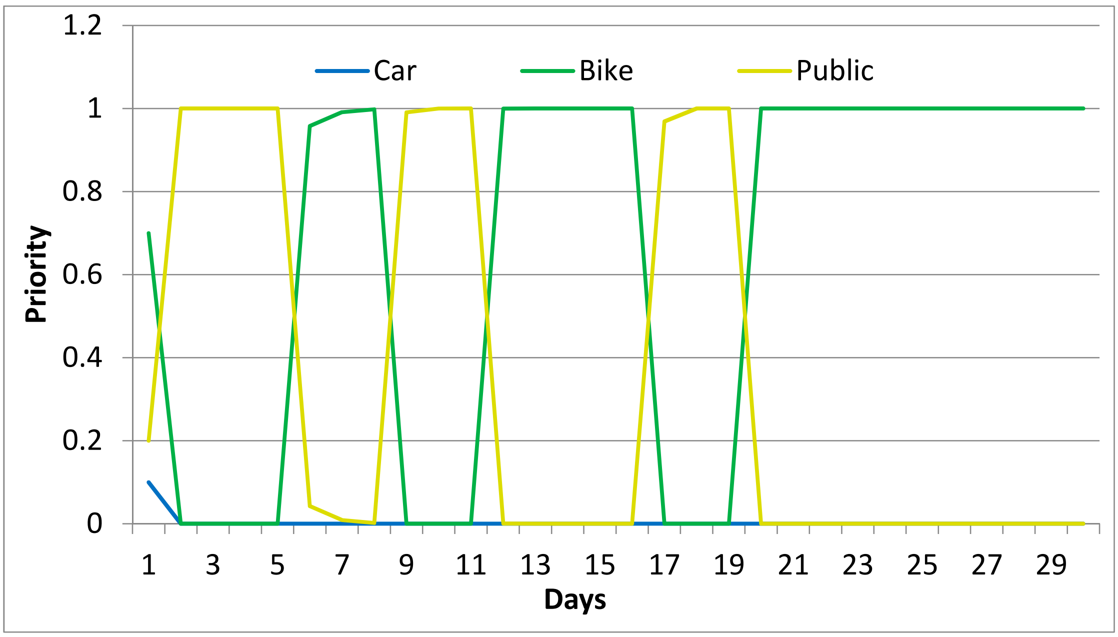

Figure 4. Changes in priorityi,k if rain is turned in and off for the agent Alfred.

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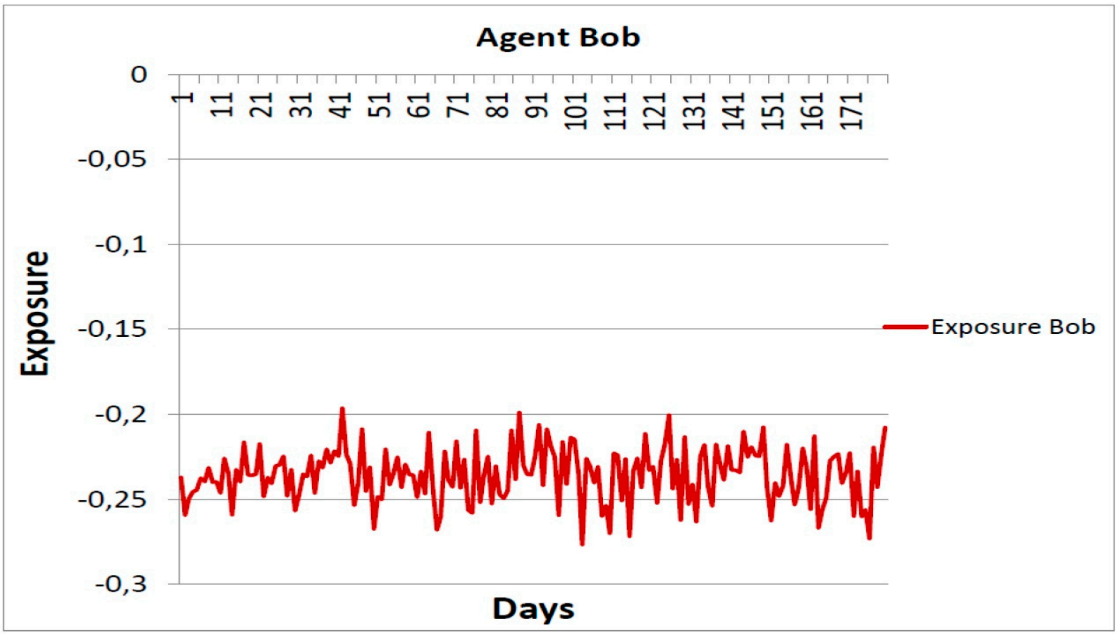

Figure 5. Changes in exposure to environmental stressors if a construction is blocking one path.

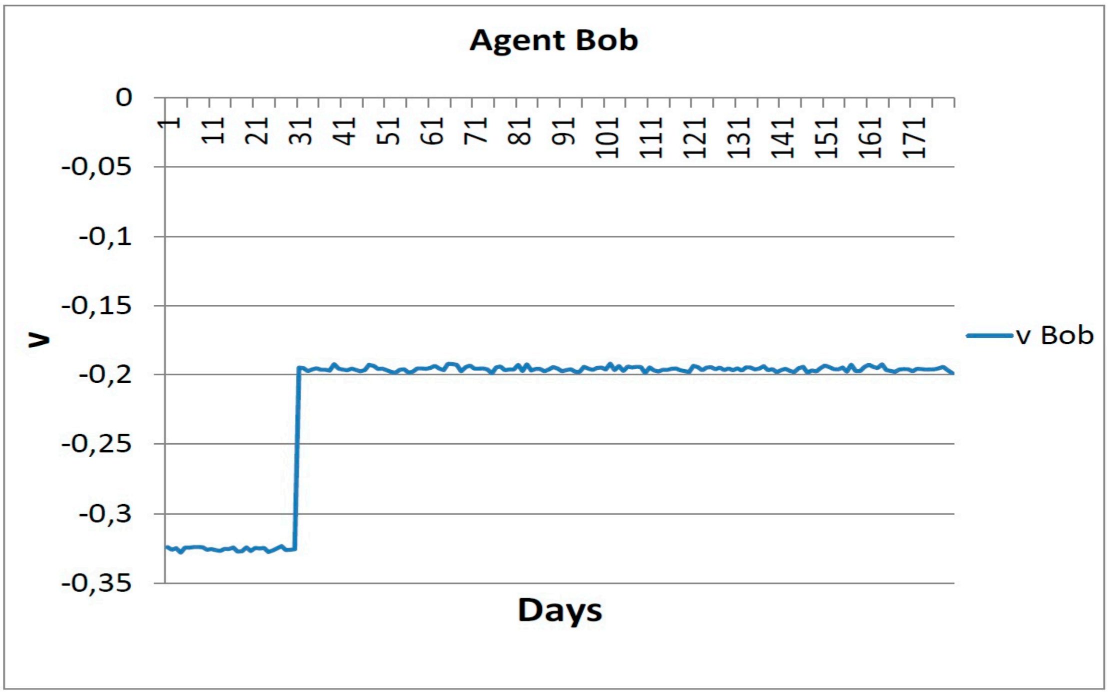

Figure 6. Changes in v if a construction is blocking one path.

A construction does only affect agents who are taking the car because one choosable path is not available anymore. A construction does not affect the exposure to environmental stressors significant but the commuting time. In Figure 5, it is visible that changes in exposure to environmental stressors are not significant for Agent Bob, who has a high priority for car (Table 4). On the other hand, Figure 6 shows that a strong change in v (Eq. 2) occurs due to a decreasing commuting time.

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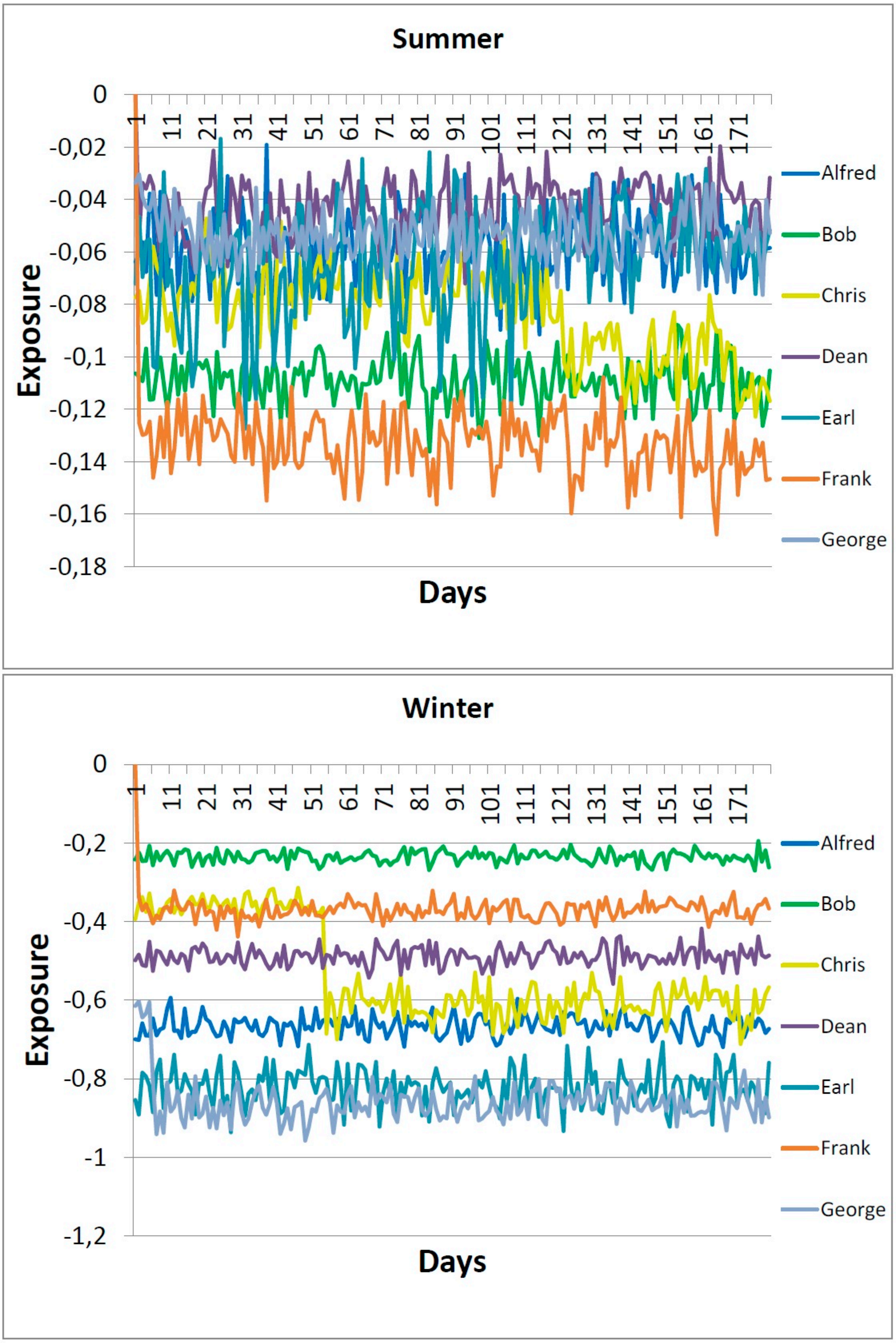

Figure 7. Exposure to environmental stressors in summer (a) and winter months (b) for all agents.

The differences in NO_2 concentration in winter and summer have a significant effect on exposure to environmental stressors (Figure 8). Several studies show that NO_2 concentration is higher in winter than in summer [68] mainly caused by more heating processes in winter months. In the first run temperature is constant but to analyze the effect of heat stress varying temperatures are introduced.

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The model shows that 42.5 °C must be reached to have the same exposure to temperature and NO_2 in winter and summer. Based on pervious temperature measurements by the German Meteorological Service (DWD) it is very unlikely to reach this value in Hamburg (highest temperature ever recorded at Hamburg-Fuhlsbüttel: 37.3 °C). Figure 8 lists the average exposure to heat stress using the NO_2 data for summer and winter. To sum it up, even the highest temperatures in Hamburg are not high enough to show the same exposure effect than the high NO_2 concentrations in winter months. However, these simulations are idealized and it is not yet clear how to compare air pollution and heat stress exposure directly e.g. with respect to health or wellbeing. Nevertheless, with the proposed ABM both stressors can be modeled and assessed in a consistent way.

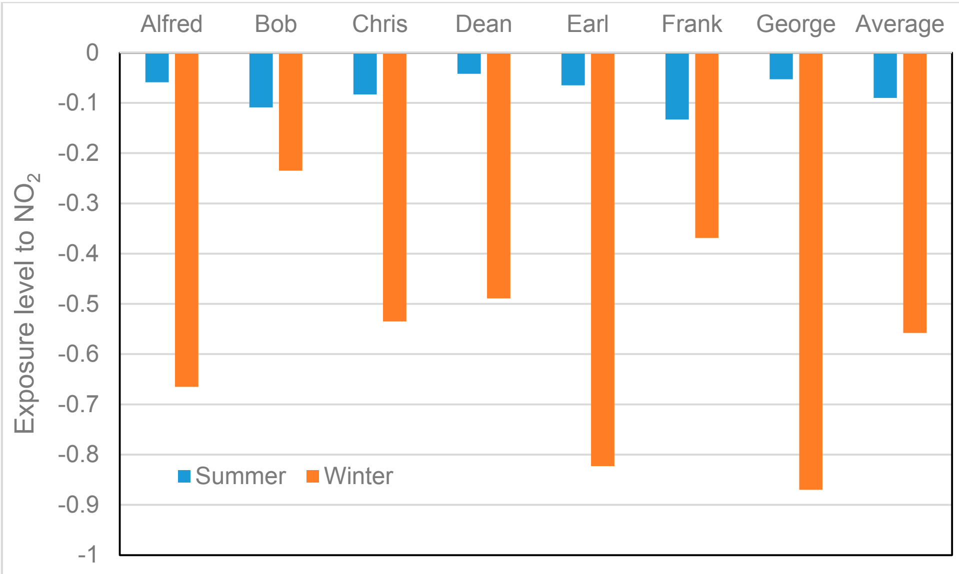

Figure 8. Individual and average normalized exposures to NO2 for summer and winter

5 Conclusion and outlooks

This paper presented an agent based modeling framework for dynamic micro-simulations of urban individual exposures to environmental stresses. Using the framework for the Hamburg scenario it is shown that it is flexible enough to handle a variety of input data and extend or replace algorithms. For example, heat stress data from model results could be employed, which will become available in the future.

Moreover, it is well possible to extend the prototype model. Therefore, extra algorithms should be added to each package to verify, manipulate, add or delete data items according to the purpose of the algorithm. Since for each new scenario different algorithms have to be used or implemented, it is of great interest that algorithms should be clearly separated from the data structure. They also should be easily exchangeable by others. The order in which algorithms are called should be flexible as well. The algorithms are collected into a sub-package of that data structure which they manipulate.

It has been argued that traditional validation methods are less appropriate for agent-based models, as by their very nature, such models are simplified representations of complex reality and indicate what may happen rather than what will necessarily happen. This caveat notwithstanding, the validity of this model has been considered in several ways as illustrated in the modeling framework and implementation sections. Nevertheless, it is only a framework. The algorithms presented for modeling are basic. Resources are needed to enhance those algorithms and to validate the resulting demand against behavioral issues. Within the UrbMod project (von Szombathely et al. 2017) data from a stakeholder survey with a focus on daily routines of urban residents in Hamburg (von Szombathely et al. 2018) and from the patients' database at the University Hospital Hamburg-Eppendorf are collected which can be used to set more realistic values for the attributes of the agents. In addition, with respect to the heat stress exposure the individual differences of the agents (age, gender) and their thermal history (e.g. time spend in sunshine) could be taken into account to model

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personal dynamic thermal indices, similar to Bruse [69] but for a much larger domain and period. In this way, the adaptive actions of an agent are linked with the exact thermal history experienced.

The purpose of this case study is not to simulate exact prediction of environmental events but to demonstrate the utility and potential of an agent-based model to be used in an exposure analysis to support environmental incident management. The conceptual approach in its current state relies on simplified assumptions and interrelationships between the social and the environmental subsystem, as well as artificial input data. This was necessary since real data are lacking and the complexity had to be limited. The main objective, however, was to test feasibility of this approach for exposure assessment and to fully understand the relevant mechanisms needed by developing a model prototype. This work also shows the importance of interaction between the transportation community and computer scientists. To satisfy the requirements concerning data management, data processing, computational design and implementation, runtime issues, etc., it is necessary to include computer knowledge into the transportation research process.

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Author Contributions: L. Emlyn Yang, Peter Hoffmann and Jürgen Scheffran designed the study; L. Emlyn Yang did the literature overview and constructed the modeling framework; Sven Rühe performed the prototype model for the Hamburg case; all authors contributed to write the paper.

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