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APPLICATION OF GIS IN MODELLING REAL TIME POPULATION EXPOSURE TO PM2.5

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ABSTRACT

Air pollution has caused many deaths globally across all age groups with most of the deaths attributed to PM2.5 which is an extremely small sized particulate matter that can travels deep in to the lungs, hit the blood stream and affect the respiratory track. This study has estimated Southampton spatiotemporal population exposure to air pollution using the Surface builder (SB) 24/7 model and a modelled air pollution data from DEFRA with a specific focus on the variation in the level of exposure to PM 2.5 by different population age groups, using GIS. After modeling the population exposure the resulted map was resampled to 200m by 200m to match the spatial resolution of the output population distribution model. The result shows that only few areas around the southern parts of the study areas (mostly residential areas with low commercial activities) have low concentration of PM2.5 pollutant. The results further identified a significant variation in the level of exposure by different population age groups with the population age group between the age of 18 to 64 (non-students) having the highest level of exposure at both 2am (55% of the exposed population) and 2pm (52%). On the other hand, the age group with the lowest level of exposure (2%), at both times of the day, is 16 to 17 years of age. 18 to 64 years old students in higher education (HE) and people of over 65 years of age are second subgroups highly exposed while the remaining age groups (0 to 4, 5 to 9, 10 to 15) show almost similar exposure (5 to 6%) in both times of the day. Overall, there is an incredible difference in exposure to PM2.5 by different age groups which reflects the level of spatial interaction by each age group.

KEYWORDS: Air pollution, population distribution model, surface builder 247, population age groups, PM2.5, spatiotemporal estimates

INTRODUCTION

The World health organization has estimated that about seven (7) million deaths occur annually due to air pollution (WHO 2016). This is because, air pollution is an invisible killer (WHO, 2016) with a great link to chronic lungs, heart, cancer, cardiovascular and respiratory diseases which eventually kill people (Daly, 1959; Menck, et al. 1974; Greater London Authority, 2012). Air pollution may be responsible for significant economic damages and numerous environmental disasters with even severe consequences, such as global warming.
Air pollution is almost in all urban areas of the World (WHO, 2016) and considering the spatial interaction of the human population in towns and cities, it is most likely that people get exposed to air pollution daily without them even noticing it. An example of this type of invisible pollution is Particulate matter (PM2.5) that is extremely small in diameter and can penetrate deep into the lungs, hit the bloodstream and affect the respiratory tract (Public health England, 2018).
On the other hand, other pollution sources such as diesel engines or smoke from vehicular traffic appears quite visible in the air. An estimate by the European environment agency showed that more than 30% of Europe's population are still exposed to air pollution (Dias and Tchepel, 2018).
In a simple definition, air pollution is the emission of harmful substances such as PM2.5, NO_2, CO_2, among others, into the atmosphere (Daly and Zannetti, 2007). These substances make humans and other living organisms, including plants, feel uncomfortable. Exposure of the human population to air pollution occurs when there is contact between people and air pollutants such as PM2.5, NO_2, CO_2 in a specific place and at a particular time (Lu and Fang 2015; van Leeuwen, et al. 2012).
To estimate the exposure of a population to air pollution, understanding the dynamics and population travel pattern is necessary (Kwan, et al., 2015). Because both air pollution and human population vary in time and space and most pollution sources such as manufacturing and traffic are most likely linked to human

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activity. Briggs (2005) investigated the spatiotemporal variability of population exposure to air pollution. He reported that most peak exposure to air pollution occurs during the day when people are expected to go to work, at work or travelling to and from work. Therefore, as people spend different time at different locations throughout the day, they encounter different pollution levels.

Most previous studies on population exposure to air pollution do not consider the complex spatiotemporal variations in population travel patterns and air pollution. For instance, Kwan, et al. (2015) argued that some previous studies used demographic data to estimate population exposure to air pollution based on an administrative structure. Such data have inherent limitations to estimating real-time exposure of population as it regards the population as static.

Furthermore, some studies used Geographic information systems to model population exposure to air pollution. Gulliver and Briggs (2005) developed the Space-Time Exposure Modeling System (STEMS), which uses GIS to estimate spatiotemporal exposure to air pollution.

METHODOLOGY:

This study adopted the SB 2/47 modelling framework (Martin, Cockings and Leung, 2009) and implement the model in the Southampton city UK, using the 2011 residential population (236,882 people) (Southampton city council 2011). The study also used a modelled air pollution data from the United Kingdom Department of Environment, Food and Rural Affairs (DEFRA), produced based on the European Union air quality directives. The human population modelling framework (Surface builder 24/7) developed by Martin, et al. (2015) uses population census data, origin and destination, labour force survey data, traffic data and other ancillary data. These data and population model choices are relevant as they consider the complex space-time variability of air pollution and the human population.

Determining pollution concentration in study area.

The air pollution data was subjected to series of preprocessing to make it ready for GIS. In order to determine pollution concentration in the study area, the study employed an approach suggested by (Jarrett et al. 2005) by dividing the entire study area into a series of regularly spaced grids 1km by 1 km. The GIS tool, 'fishnet', was used to accomplish the task.

The “fishnet tool” available in Arc GIS allows creating a regularly spaced grid with the spatial extent, the number of rows and columns, the coordinate of the output grid, and each cell's size. This is to ensure that the size of the grid cell corresponds to a 1 km by 1 km grid by implication having one grid to represent each of the pollution concentration points with each of the pollution concentration points falling at the centre of each fishnet grid.

After executing the create fishnet command, a spatial join operation was conducted to join the grids to the point’s pollution data representing the pollution concentration. The join output represents a 1 km by 1 km grid representing the pollution concentration of the study area.

The output was then converted to raster and resampled to 200m by 200m to match the spatial resolution of the output population distribution model. This process produced a 200m-by-200m pollution concentration map of the study area.

RESULTS

Figure 1 below show the concentration of PM2.5 in the study area. Areas around Bitterne, Woolston and some parts of Basset have the lowest concentration of PM2.5 in the study area. Therefore, this reflects the low presence of significant pollution sources, a relatively low traffic density and low industrial and commercial activities. On the other hand, Bargate, Bevois, Freemantle, Redbridge and Millbrook have the highest concentration of PM2.5 in the study area. In the case of Barget, the presence of large shopping malls, high population concentration during the day, heavy traffic and other commercial activities may be responsible for the high values. At the same time, Freemantle has the highest pollution concentration, which is probably a reflection of the conglomeration of many commercial activities. For example, the port of Southampton, which is one of the primary pollution sources, is in this ward.

Furthermore, Bargate is home to the Southampton train station, the West que, and many malls, retail shops, commercial hubs, and banks. This conglomeration of different activities made the city crowded and the traffic level very high. Also, the presence of malls means HGVs are frequently plying the roads in the ward to deliver goods to malls and therefore contribute to pollution of the ward. The following sets of areas with slightly lesser PM2.5 concentration are Redbridge, Freemantle, Basset and Coxford. These areas, especially Redbridge, have some traces of industrial activities. Areas with slightly moderate pollution concentrations are Portswood, Harefield, Sholling and Swaythling. These are primarily residential areas with a few commercial activities such as malls.

Classification of the study area into high and low pollution concentrations of PM2.5 based on the WHO threshold.

Figures 2 and 3 below show areas with high pollution concentrations and those with low pollution concentrations in the study area. Woolston (6.6 ugs/m3), Swaythling (9.1 ug/m3), Sholing (8.4 ug/m3), and Bittene (3.5 ug/m3) all have low pollution concentrations based on the threshold used in the classification. On the other hand, areas with a high concentration of PM2.5 are Bevois (15.3 ug/m3), Bargate (14.4 ug/m3), Shirley (13.5 ug/m3), Redbridge (13.2 ug/m3), Portswood (10.2 ug/m3), Peartree (13.9 ug/m3), Millbrook (11.8 ug/m3), Harefield (10.9 ug/m3), Freemantle (12.9 ug/m3) and Basset (12.6 ugs/m3). From the description above, most of the study areas have high concentrations of PM2.5.

Estimating the total population exposed to pollution in the study area PM2.5

Figures 3, 4 and 5 show the total population exposed to PM2.5 at 2 am and 2 pm, the percentage of population exposed to PM2.5 at 2 am and the percentage population exposed to PM2.5 at 2 pm, respectively. The population age between 18 to 64 non-students is the predominant population structure exposed to air pollution concentration at both times of the day. For instance, at 2 am, the estimated exposure of the age group is about 55 per cent of the entire exposure, which reflects the total number of the population structure in the study area. Furthermore, at 2 pm the age group shows a similar level of exposure with an even slightly lower level of exposure, about 52 per cent. On the other hand, the age group with the lowest level of exposure (2percent) at both times of the day is 16 to 17 years of age.

Furthermore, age group 18 to 64 students in higher education (HE) and over 65 years of age are second subgroups based on the level of exposure. These two different age groups have slightly similar population exposure. For instance, at 2 am, both age groups have an exposure of 13 per cent of the total exposure of the entire population. On the other hand, the 2 pm exposure shows age group 18 to 64 (HE) having 17 per cent of the total exposure compared with just 12 per cent for the over 65 population. The level of exposure of this population age group reflects their spatial interactions over the study area. While 18 to 64 HE shows high exposure at 2 pm time reflecting the presence of the students around schools which is outside the accommodation area, the over 65 show the same exposure at both times (13 per cent); this may likely reflect the fact that the ageing population have shallow spatial interaction. Three remaining age groups used in the study (0 to 4, 5 to 9, 10 to 15) show almost similar exposure estimates, with each having 5 per cent in each time of the day except age 0 to 4 having about 6 per cent.

Overall, there is an incredible difference in Exposure to PM2.5 by different age groups. The level of exposure shown seems to reflect the level of spatial interaction by each age group.

DISCUSSION

One of the study's significant findings is the differences in Exposure to PM2.5 among the population age groups. The most exposed population age group to PM2.5 concentration is age 18 to 64 non-students. This finding is like the suggestion made by Briggs (2005), that peak exposure by population is recorded during the day, which corresponds to the period of people working, going to work or school.

Furthermore, concentrations of PM2.5 in the study area vary significantly, and the population's level of exposure seems to be determined by it. For example, most of the study area is classified as having a high concentration of PM2.5 base on the WHO threshold of 10 **(**ug/m3). Therefore, the population's exposure to particulate matter (PM2.5) reflects this concentration, especially the 18 to 64 years non-students.

On the other hand, children population age 0 to 4, 5 to 9 and 10 to 14 showed similar Exposure to PM2.5 about 5 to 7 per cent each but compared with the age 18 to 64 who mostly spend day time going to work, and it is relatively low. Despite the lower exposure to pollution concentration by children, it has been reported by UNICEF UK, 2018; The Guardian and Green peace U.K. 2017; UNICEF UK, 2016, that children are the most vulnerable groups of the population to air pollution. Their height makes them more vulnerable to ground-level pollution, especially ground-level pollution from vehicles. In addition, their developing bodies are more likely to be damaged by air pollution.

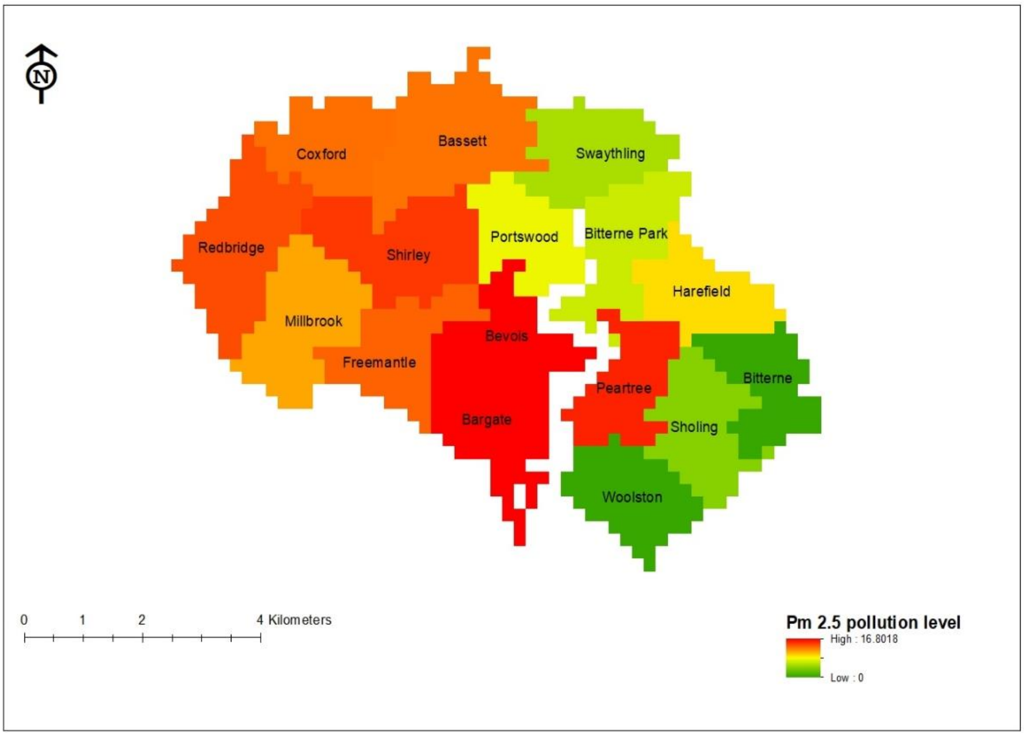

Figure 1: PM2.5 concentration in the study area.

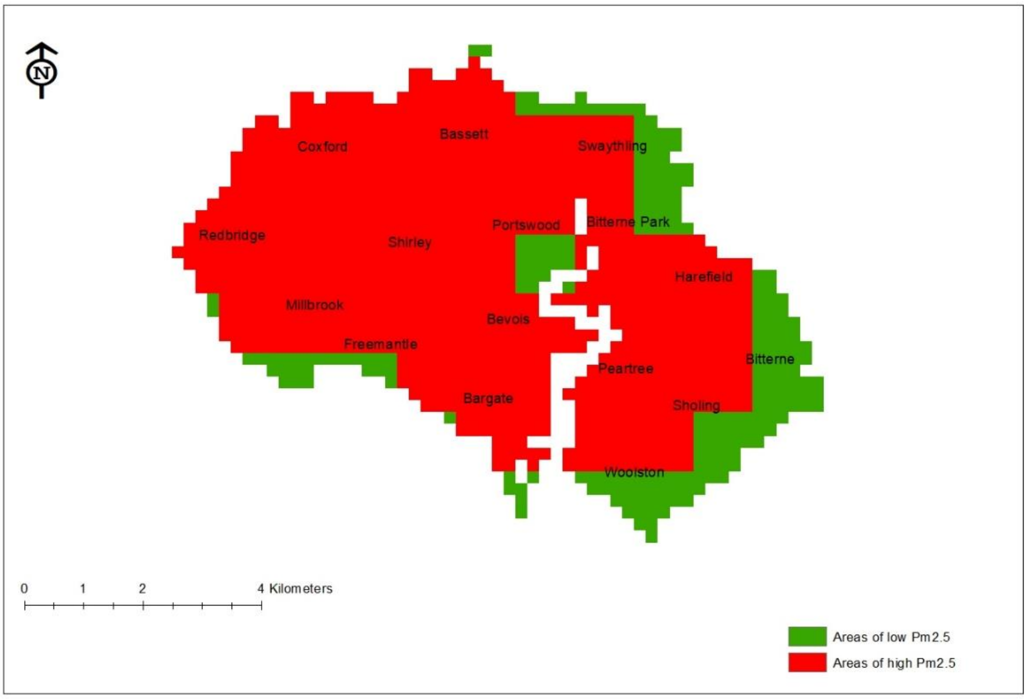

Figure 2: Areas of low and high PM2.5 concentration

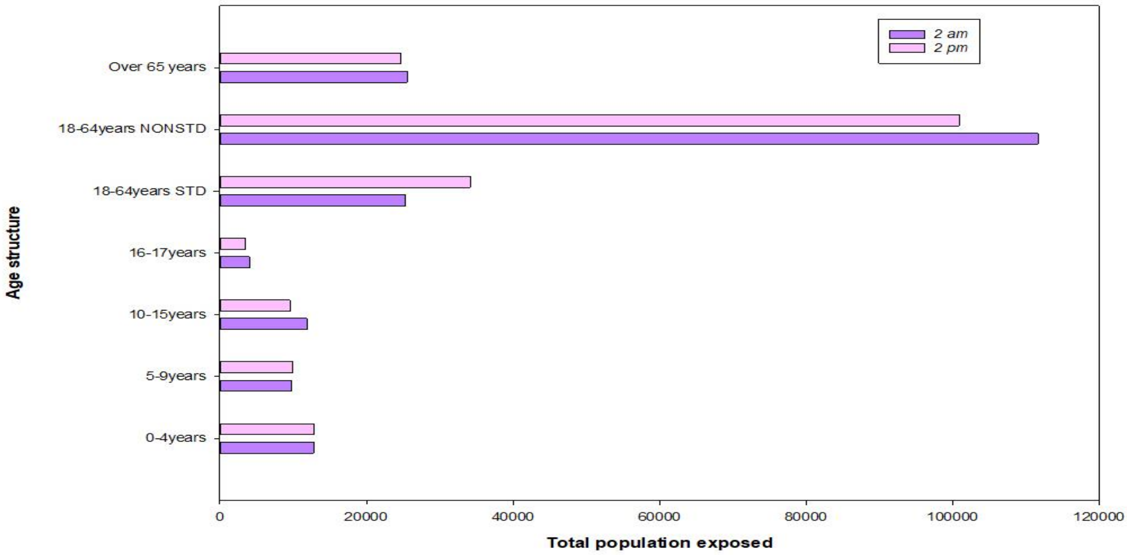

Figure 3: Total population exposed to PM2.5 at different time of the day

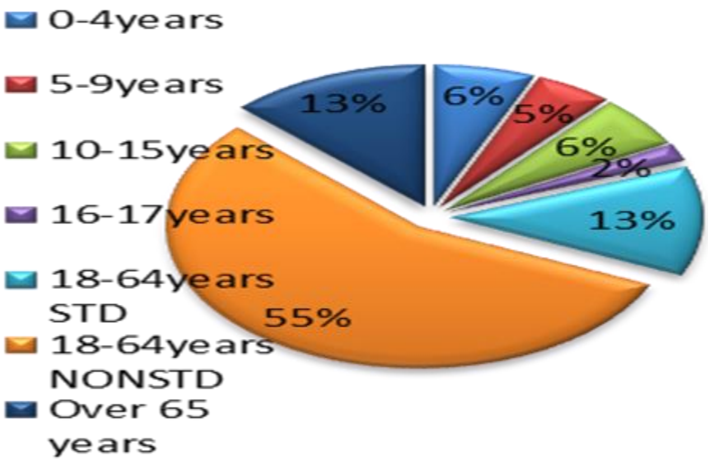

Figure 4: Percentage of population subgroup exposed to PM2.5 pollution concentration at 2 am.

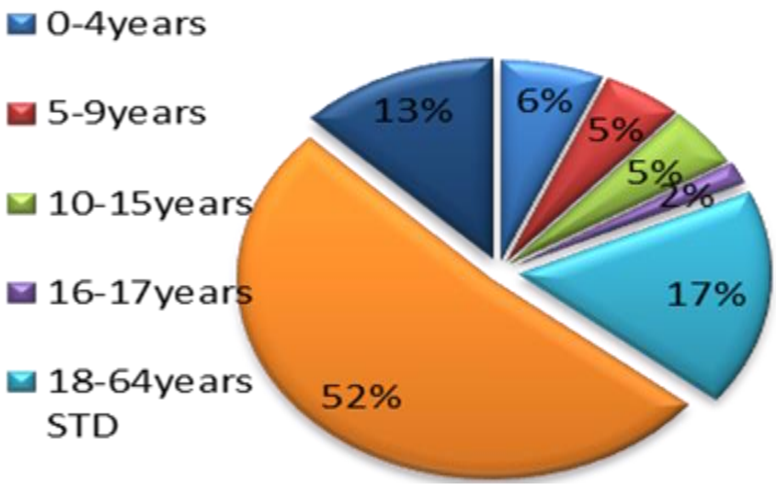

Figure 5: Percentage of population subgroup exposed to PM2.5 pollution concentration at 2 pm.

CONCLUSION

In conclusion, this study has estimated Southampton spatial-temporal population exposure to air pollution using the Surface builder (SB) 24/7 model and a modelled air pollution data from DEFRA. A specific focus was made on the variation in the level of Exposure to PM 2.5 by different population age groups.

The study reveals a significant variation in the level of pollution concentration in the study area. The wards were classified into two; based on the level of concentration of PM2.5 and about eleven wards which include: Bevois, Bargate, Shirley, Peartree, Redbridge, Portswood, Millbrook, Harefield, Freemantle, Oxford and Basset were found to have an exceedance of the concentration of PM2.5. On the other hand, the study further estimated the concentration of NO_2 in the study area and revealed that only Bargate and Bevois were found to have high concentrations.

In addition, the population distribution of the study area at 2 am showed a clear reflection of the residential distribution of the study area. The 2 pm distribution, on the other hand, reflect the presence of the population in specific destinations such as schools, workplaces etc. Specifically, age group 18 to 64 non-students were mainly concentrated around Bargate, Bevois and Shirley, with Bargate having the highest concentration (19700). Furthermore, the age group 18 to 64 students were mainly concentrated around the two Universities in the study area. Other age groups such as 16 to 17, 10 to 15 and 5 to 9 were observed mainly around the school's location, ranging from six form colleges to secondary and primary schools. However, the over 65 years and 0 to 4 years did not show a different distribution from the 2 am.

The Highest Exposure to PM2.5 was recorded amongst the age group 18 to 64 non-students, representing 55 per cent and 52 per cent at 2 am and 2 pm, respectively. The students in the higher education population were the second most exposed group, with about 17 per cent at 2 pm and 13 per cent at 2 am. Furthermore, the over 65 year's group show a similar level of exposure representing (13percent) PM2.5 at both times of the day. The children population 0 to 4, 5 to 9 and 10 15 showed some level of exposure which is about 5 to 7 per cent. Age 16 to 17 were observed to have the lowest exposure (2 per cent)

The major limitation of this study was the use of coarse resolution pollution data. A more exemplary resolution pollution data such as hourly mean concentration on a high resolution and an hourly spatiotemporal population distribution would have made it possible to identify more details.

The findings of the study would inform policies aimed at improving human population health and wellbeing and ambient air qualities improvement in order to make cities habitable and resilient. Therefore, the study will accelerate the attainment of Sustainable Development Goals SDGS goals 3 and 16. The study further demonstrated the capability of GIS to answer human exposure questions. Such as what population age group are exposed to pollution, how has this exposure varied amongst age groups.

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