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A DAY-NIGHT POPULATION EXCHANGE MODEL FOR BETTER EXPOSURE AND CONSEQUENCE MANAGEMENT ASSESSMENTS

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1. INTRODUCTION

Emergency response in the event of a hazardous chemical or biological material release in an urban area needs to occur on two time scales: 1) real time response to a known event and 2) delayed response to latent events which are not expressed at the point of release. The latter is particularly important in the case of chemical or biological material releases which may go undetected until patients begin showing up in hospitals due to the delayed pathogenic or toxic response to the organism or chemical in question. In order to reconstruct such undetected events, trace exposed individuals and provide adequate treatment and prophylaxis to quell any burgeoning epidemic, emergency responders need to be able to estimate who was exposed at the time of event and where they may expect to see them enter the public health system – i.e., determine which hospital they will eventually arrive at. Definition of expected hospital arrivals of new cases requires being able to estimate migratory patterns of urban citizens under normal and emergent conditions. There are many simulation systems capable of the simulation of urban mobility patterns. While these systems are capable of high spatial and temporal resolution urban mobility simulation, they often require significant computing resources and are difficult to use in a near real time environment.

In this research, we present a model that fuses US Census Bureau population mobility data with a raster based day-night population data model in a decision support system for fast turnaround analysis of public health emergencies. This approach is an improvement over our prior work in which we created static representations of day-night, indoor-outdoor population for the continental USA and Hawaii at 250 m grid resolution (McPherson and Brown, 2003; McPherson and Brown, 2004). Our previous static data models were developed to improve exposure assessments for hazardous airborne contaminant releases and were akin to other research by Lo (2001), Yuan *et al*. (1997), Dobson *et al*. (2000), Harvey (2002), and Langford and Harvey (2001). In this research, we use our static population models with data on population dynamics to support consequence assessment and emergency response.

To construct such a model, we decompose human population mobility patterns into three primary migratory forcing functions: the journey to work, the associated journey to home, and the journey to the hospital. The former two migratory patterns are the two major patterns that most adults conduct throughout their lives. The latter defines where affected people may enter the public health system.

2. BACKGROUND

We have developed a raster-based day-night, indoor-outdoor population database for the continental USA and Hawaii at 250 m grid resolution (McPherson and Brown, 2003; McPherson and Brown, 2004). Figure 1 shows the daytime population data model. Data models were created in raster format to facilitate use with urban air dispersion codes that are primarily grid-based. The population data models account for the shift of population from place-of-residence to place-of-work during the workweek. For the nighttime data model, population from 2000 US Census blockgroups was redistributed to rasterized residential roads from the commercially-available GeoData Technologies (GDT) roads database. Population was placed at roads instead of the more common areal average approach to reduce errors that may occur with that approach in sparsely populated regions such as rural areas.

The daytime population database is composed of a worker and daytime residential population. The shift in population during the day is determined using the 2000 Census Transportation Planning Package (CTPP) Part 3, which details worker flow from one region to another at the census tract and county level. Workers are placed in their destination tracts by location coefficients derived from employee counts in the State Business Directory, also a commercially-available database. Each dataset represents the peak population in 12 hour intervals, i.e., day and night. The daytime data model represents peak populations during the work week and the nighttime data model represents peak residential populations. Although the data are most applicable to workdays, the nighttime population data model also represents the peak population for weekend population. Future enhancements will involve finer spatial and temporal breakdown of the population including morning and evening work commutes, school (K-12 and higher learning) and retail shopping. Furthermore, greater resolution in workplace temporal patterns will be included to capture shift work population.

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Figure 1. Day-Night Population Data Model for the continental United States at 1km grid cell resolution

In 2005, we added an indoor-outdoor component to the data model. This first generation database of the indoor and outdoor components of the day and night population (McPherson *et al.*, 2005) was created by extracting activities at home and work locations from the National Human Activity Pattern Study (NHAPS) contained within the US Environmental Protection Agency (EPA) Consolidated Human Activity Database (CHAD). Indoor/outdoor fractions were derived from the NHAPS data by separating the activity data by location (i.e., indoors versus outdoors at residences and workplaces) and time (i.e., daytime versus nighttime) and calculating the ratio of total person minutes of people conducting outdoor activities relative to the total person minutes of people conducting any activity at certain location types – i.e., residential or commercial. The resulting fractions were then used to disaggregate the daytime residential population, the daytime workplace population, and the nighttime residential population grids into indoor and outdoor components, which were subsequently combined to define total daytime and nighttime indoor and outdoor populations.

3. Day-Night Population Exchange Methodology

In order to determine the full extent of impacts from a chemical or biological release, emergency responders need to be able to track exposed individuals to their homes (for daytime releases) or to their workplaces (for nighttime releases). The Day-Night Exchange model uses hospital data and data from the US Census on journey to work along with our day-night population data models to plot exposed population during an event, their subsequent travel to home or work, and eventual admittance to a hospital.

The 2000 Census Transportation Planning Package (CTPP) Part 3 packages contain data relevant for studying the commute to work in the United States, such as the number of workers traveling from location to location including home tract to workplace tract, the means of transportation, travel time, financial status, and the number of carpools. We utilize only the data on the number of workers that travel from tract to tract to determine population exchange between day and night locations. Records describing worker flow to unspecified tracts or outside of the country are discarded. The extracted relevant data are stored in a work flow table with three columns: a unique identifier, and census tract of residence, a unique identifier for the tract of employment, and the number of workers that travel from the former tract to the latter. By accessing the worker flow records by their home tract, workers can be moved from home to work, and by accessing the records by their work tract, workers can be moved from work to home. In each case, the data are used to create a probability matrix defining the likelihood an individual moves from their current tract location to other tracts associated with the initial tract by the workflow data.

Figure 2 demonstrates how workers in a particular tract can travel between home and work and from work to home.

In the population exchange model, population is routed to hospitals using techniques for plotting affected populations at their homes and defining hospital service areas. Affected population within their home tracts are rasterized using a location coefficient grid derived from the nighttime population raster. This affected population is then routed to hospitals based on a set of hospital service areas. Hospital service areas are derived using a Voronoi Tessellation and hospital latitude and longitude coordinates. At present, we are assuming all affected individuals will be routed to a hospital. In the future, we will include use rates to improve the demand on hospital services estimate.

4. Results & Discussion

The population exchange model has been completed and can be applied in a wide array of event types. As an illustration, we present the following case study based on a hypothetical accidental air release in the Chicago area of a chemical that is colorless, odorless and does not elicit a health response for 12 hours.

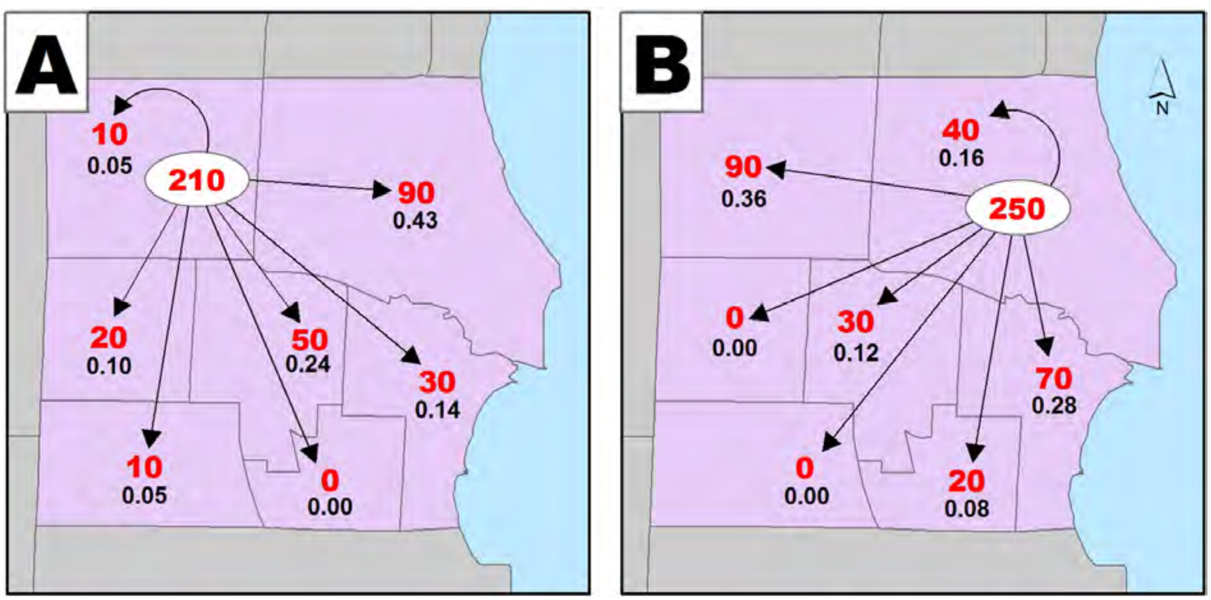

Figure 2. Illustration of using the worker flow table to apportion workers. In a), 210 workers are being distributed from their homes in the northwestern tract to tracts that they work in. The number of workers is shown in red, and the ratio of workers moving to a destination tract from the origin tract is shown in black. Note that 10 workers work in their home tract. In b), 250 workers are shown leaving a northeastern work tract to their place of residence. Notice that the number of workers traveling between the northeastern and northwestern tract are the same in both figures, but the fraction of the total worker flow is different in each case.

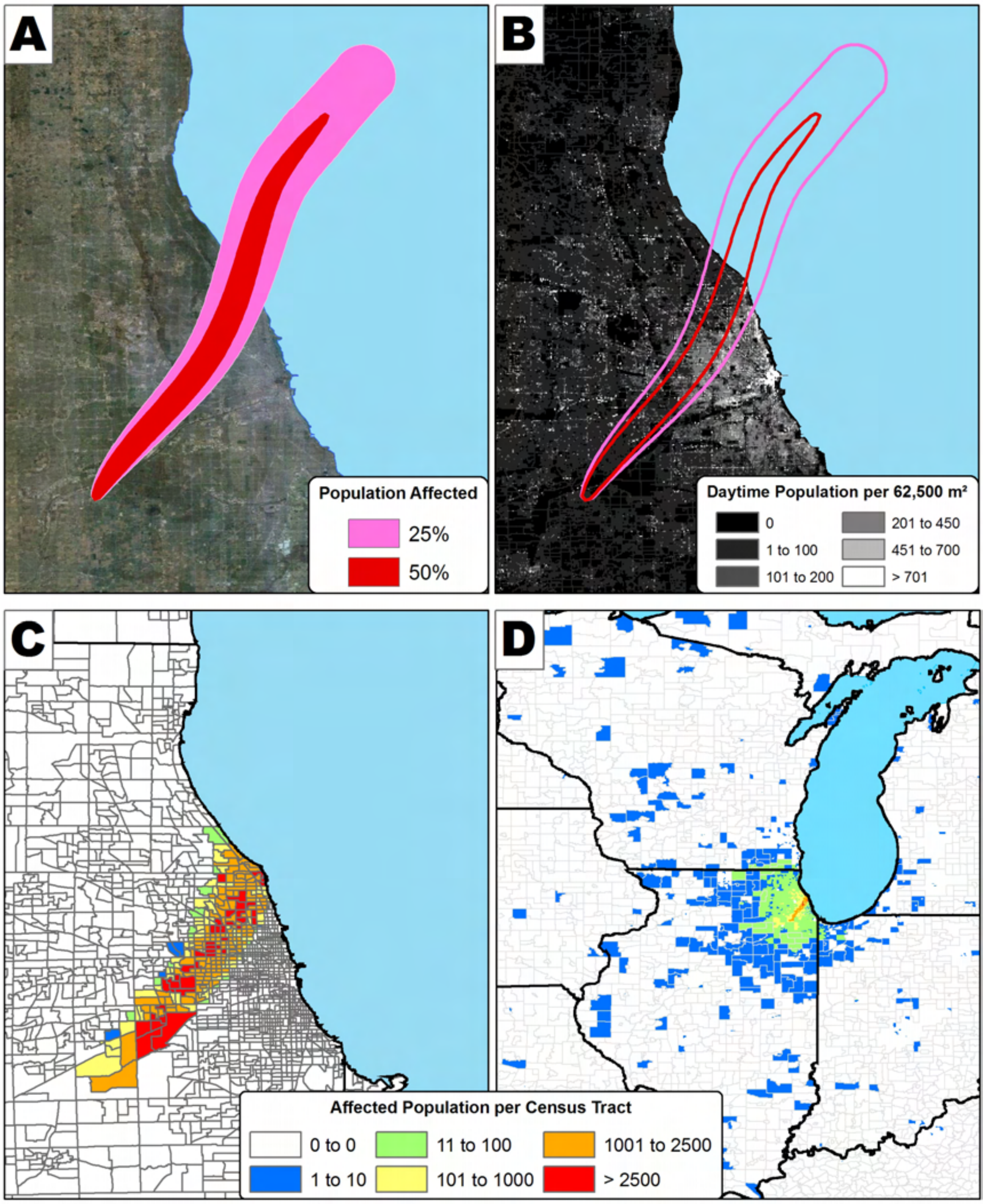

Figure 3. Population Exchange Model applied to a hypothetical plume release in the Chicago area.

Figure 3 shows the results of our case study. In panel A, an accident has occurred releasing chemical X. The plume travels to the Northeast due the predominant wind condition. For this example, the innermost (red) region of the plume is a contour where the dosage causes a health effect in 50% of the underlying population and the outermost (pink) region is the contour where the dosage causes a health effect in 25% of the population. The population affected by the chemical accident is determined by overlaying the plume contours onto the daytime residential and worker population grids for the Chicago area as shown in panel B. The exposed population is calculated using the 250m resolution population grid, which is then summed to census tract level as shown in panel C. Given the event is not detectable by the human senses, the population exposed will likely not know that anything has occurred since health effects are also delayed. Workers exposed to the plume may travel home without knowing they have been exposed.

Using the exchange matrix database, a new affected population map can be created that represents where affected people will be located at the end of the day as shown in panel D. Clearly, the spatial distribution of exposed persons covers a much larger area than that originally calculated under the plume. This has important consequence management implications. For events that are undetected, the spatial extent of the necessary response can cover hundreds of kilometers whereas the spatial extent of the initiating event (i.e., the plume dispersal) is approximately an order of magnitude smaller. This increased spatial extent complicates decisions on where to distribute medicine or other resources, and in the case of contagious organisms can severely limit the public health system's ability to contain an outbreak. Results from the hospital routing tool support these contentions. Figure 4 shows the distribution of affected population in census tracts. Figure 5 shows how those individuals will be routed to hospitals. Hospitals as far as 150 kilometers from the center of the release can expect up to 25 cases of exposure related ailments.

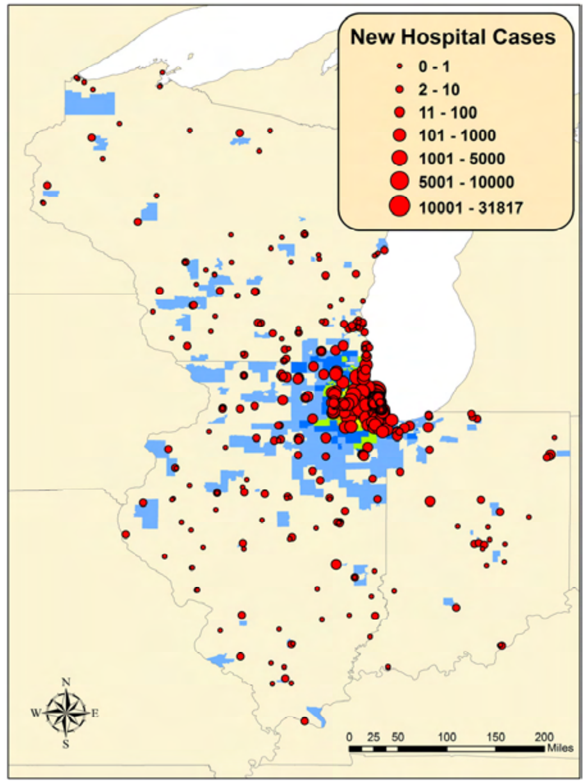

Figure 5. Affected population spatial distribution at hospitals.

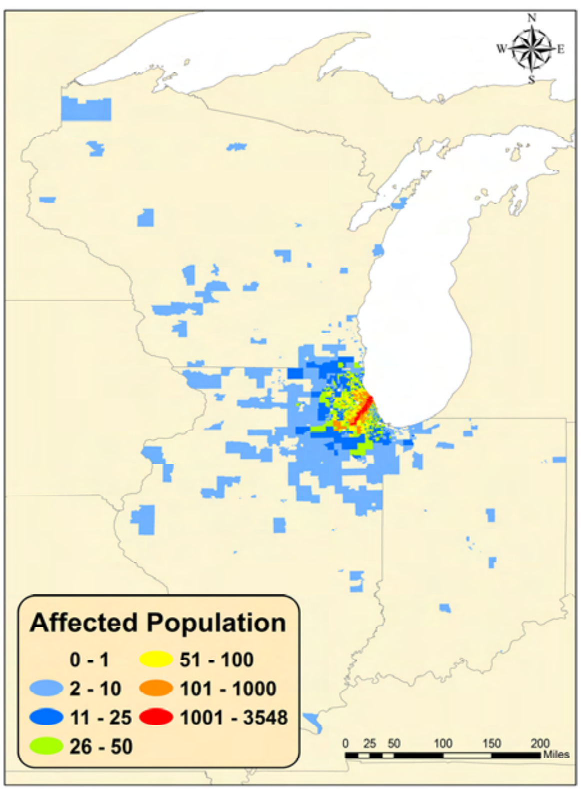

Figure 4. Affected population spatial distribution after the journey to home.

As with any modeling study, the quality of the output is no better then the quality of the input. In this case, the model is highly reliant on census data. Although the US Census is one of the best in the world, issues can arise with our use of these data. First, the CTPP worker flow data was a survey in which the respondent was asked to note their work location in the week prior to the survey. This can result in the generation of some large distance workflows that in reality occur infrequently. The indoor and outdoor databases also have a number of limitations, including the errors inherent in the reporting and recollection methods used in many human activity pattern studies. Furthermore, in our first generation product, regional and seasonal differences in activity information were ignored. Finally, the categorical indoor and outdoor values presented in this report represent a 12-hour temporal aggregation of the activity data. Therefore, local peaks in time and space may be reduced. Also at present the hospital routing tool routs people based on their home locations. While it may seem logical that most individuals who are sick are going to stay home prior to deciding to go to a hospital, undoubtedly some individuals end up heading to the hospital from work. At present, we are not representing people who go to work prior to hospitalization.

6. SUMMARY

In this research, we have presented a model that routs people from home to work at the aggregate level of a census tract. These data are used in conjunction with a day-night population data model to define the populated impacted by an event such a chemical release, to track the exposed population probable spatial distribution in the subsequent 12 hour period, and to rout them to hospital once symptoms may be presented. This capability is useful for studying airborne contaminants that have delayed health effects or are contagious. For these cases, determining the population within the contaminant plume is just the first step; knowing where the dosed population ends up 12 hours later may be just as important from a consequence management perspective. For example, contagious agents with a considerable latency period will not cause an immediate impact on the exposed population. In those cases, the impact of the event will not be seen until exposed populations become ill and begin showing up at hospitals. The model was shown to be of possible value to decision makers who need information on the projected impact on hospitals, how a disease might spread, or where to distribute medical supplies.

T**7. ACKNOWLEDGEMENTS**

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