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DETERMINATION OF THE SPATIAL AND TEMPORAL DISTRIBUTION OF POPULATION FOR AIR TOXICS EXPOSURE ASSESSMENTS

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1. Introduction

Assessment of the effects of air toxics releases in urban areas requires accurate definition of population exposure. There are two critical components in such population exposure assessments: 1) the quantification of the plume dispersal and 2) the quantification of the spatial and temporal distribution of population underlying that plume. Urban buildings in downtown areas complicate both of these issues. Plume dispersal around urban buildings is highly complex and the occupancy status of those buildings changes with people migrating from indoors to outdoors and from residence to workplace. Population datasets used for urban exposure assessments need to reflect these urban population migrations. Currently, the vast majority of available population datasets are based on residential populations and do not account for daily migrations from residence to workplace or the indoor/outdoor status of those people. For example, in the United States, the population data readily available from the U.S. Census Bureau is based on households (U.S. Census Bureau, 2000). The use of residence-based population databases in exposure assessments can produce significant inaccuracies in morbidity and mortality estimates especially when considering daytime releases in downtown areas. In this research, we demonstrate a method for estimating urban daytime population and for improving nighttime population using US Census, infrastructure, and business demographic data in a GIS. We also develop techniques for estimating the fraction of those populations that are within buildings versus outdoors during the day and night using the US Environmental Protection Agency Consolidated Human Activity Database (CHAD). These methods have been applied to create national grid datasets of daytime and nighttime indoor/outdoor populations with a 250m resolution. We then demonstrate the value of these datasets by estimating the population exposed during a hypothetical chemical spill in Houston, TX.

2. Prior Work

There are two primary methods for constructing population datasets: 1) Demographic counts and 2) Geographic Information Science (GIS)/remote sensing. Demographic counts, e.g., the U.S. Census, are labor and time intensive efforts to enumerate people living in predefined geographical zones. These surveys are conducted for multiple purposes, but the primary focus of data collection is housing units and the people living therein. GIS/Remote sensing techniques use statistical methodology and empirical relationships between population and topography, coastlines or human infrastructure to estimate population distributions from geographic data and remote sensing imagery (Henderson and Xia, 1997; Lo and Welch, 1977; Iisaka and Hegedus,1982; Lo, 2001;Yuan *et al*., 1997; Dobson *et al*., 2000; Harvey, 2002; Langford and Harvey, 2001). The majority of the datasets derived in these research efforts cover small areas in the United States or portions of other countries. Dobson *et al*. (2000) did create a dataset that covered the entire globe, but the 1-kilometer resolution used in that dataset is insufficient for urban exposure analyses.

Previous research has shown that diurnal shifts in population can be accounted for in a spatial database. Dobson *et al.* (2000) constructed a global population database, known as LANDSCAN, at a 30 by 30 arc-second resolution (approximately 1 km grid cells in the lower latitudes) that accounted for diurnal movements of population in order to improve emergency response activities. They distributed country or province population to grid cells using a probability coefficient based on slope, proximity to roads, land cover, nighttime lights, and an urban density factor. Population in urban areas was adjusted to account for urban density using NGDC nighttime lights and Census P-95 Circles data, but they were not able to account for business/employee demographics in their population estimation.

3. Methodology

We have created a preliminary estimate of the diurnal temporal shift in population due to employment including the definition of fractions of people indoors versus outdoors. To accomplish this, separate population grids for nighttime residential, daytime residential, and daytime workplace population were created using existing demographic data and GIS. These grids were then combined with human activity pattern data compiled into separate indoor and outdoor components within different classification frameworks to define the temporal and spatial distribution of outdoor and indoor populations.

We constructed day/night - indoor/outdoor population databases using data available for the entire U.S. from the U.S. Census Bureau, the Environmental Protection Agency, Geographic Data Technology (GDT), Navigational Technologies (NAVTECH), and the American Business Directory, Inc.

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3.1 Databases

As noted above, five sources of data were used to construct the day/night - indoor/outdoor population datasets. Table 1 lists the sources and data types of the databases used in this study.

Table 1: Datasets used to construct day/night indoor/outdoor population datasets.

Database	Source	Date	Data type
StreetMap USA	ESRI/GDT	1998	Vector Polyline
NAVTECH Premium Streets Data	NAVTECH	2003	Vector Polyline
State Business Directory	American Business Directory	2000	Vector Point
Census Blockgroups	US Census Bureau	2000	Vector polygon
Census County to County Journey to Work	US Census Bureau	2000	ASCII Text Table
Consolidated Human Activity Pattern Database	US Environmental Protection Agency	2000	MS Access

Three general types of data were used: 1) census enumeration data 2) physiographic data, and 3) human activity diary data. The census enumeration data provided the population count to be disaggregated and the physiographic data provided the spatial units to which the census enumeration data were disaggregated. The human activity diary data were then used to define the fractions of people indoors versus outdoors for certain activity types. In this research, the 2000 U.S. Census data in vector format were used as the starting point from which populations were shifted from residence to workplace. The decennial census defines the residential population of the United States at varying levels of geographic precision. The census blockgroup data, the second highest resolution dataset from the census, were used in this research. Census blockgroups are clusters of census blocks containing from 600 – 3,000 people. The blockgroup data define the urban nighttime population per polygon. GeoData Technologies (GDT) road network data were used to create a grid of location coefficients that were used to spatially disaggregate the census blockgroup.

Workers from the residential population were then routed to businesses within their county of work using the U.S. Census "County to County Journey to Work" data coupled with the American Business Directory, Inc. data. The American Business Directory creates a commercial and industrial business database for the United States called the State Business Directory (SBD). The SBD is a commercial database containing information on approximately 12,000,000 businesses in the United States. The SBD is constructed from yellow pages directories, SEC annual reports, local, state and federal government data and verified by extensive telephone research. Each record in the database contains the company name, address, geolocation (latitude-longitude), type of business and a range of the number of employees. Business types in the database are defined by 6 digit Standard Industrial Classification Codes (SIC). The SBD data were used to create a set of location coefficients that were used to spatially disaggregate the county worker data. The U.S. Census "County to County Journey to Work" data within the U.S. Census Transportation Planning Package defines the number of people that migrate from one county (i.e., their county of residence) to another county for work. Figure 1 shows an example of the county to county worker migration data in Utah.

The county data were used because they are the best available data on worker counts that cover the entire United States. The U.S. Census Transportation Planning Package does have a worker flow dataset with a higher spatial resolution based on census tracts, but those data are not yet available from the 2000 Census.

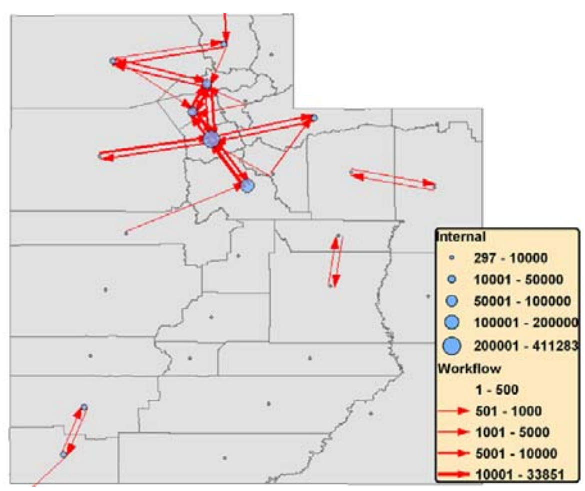

Figure 1. County to county worker flows in Utah. The graduated blue points represent the population working within their county of residence. The graduated red arrows represent the worker flow from county to county. Although county workflow below 500 people is excluded in this figure, all worker flows were used in the daytime population model development.

The fraction of population indoors and outdoors was defined using the Environmental Protection Agency Consolidated Human Activity Database (CHAD). CHAD is a Microsoft Access based database available through the National Exposure Research Laboratory (http://www.epa.gov/chadnet1). CHAD version 1.043 released in 2000 was used in this study. CHAD is a master database that contains human activity data from thirteen different surveys conducted by various organizations throughout the past 15 years. The surveys in CHAD represent nationwide and regional activity information collected by various public research organizations and universities throughout the country. Some studies, such as the Valdez Alaska study, represent a small population sample and consequently limit the extrapolation of the activity information to wider regions of the country. Thus, for the purposes of our nationwide indoor/outdoor population database construction, the most comprehensive study available within the master database, the National Human Activity Pattern Study (NHAPS), was used. NHAPS was undertaken by the EPA from October 1992 to September 1994 (Klepeis et al., 1995) and included activity information from 9,386 participants aged 0-93 from each state. Data for the NHAPS study was collected using the recall method (McCurdy et al., 2003). EPA interviewers phoned study participants each day and asked them to recall their activities for the previous 24- hour period. The advantage to this method was that interviewers could ensure no activity gaps exist in the 24-hour period while the disadvantage was that activity information was limited to the participants' recollection of their daily events. 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.

3.2 Nighttime Residential Population

Nighttime residential population databases for the United States are freely available from the U.S. Census Bureau. Although these vector data represent one of the most complete population databases available, a few modifications were made to enhance the data for exposure assessments. The original vector data assumes an areal average of population across the entire polygon. For large polygons with low population (e.g., rural areas), an even distribution of population across the entire polygon is in most cases a poor approximation. In our methodology, population is attributed to roads, i.e., evenly distributed based on the population per road grid cell within a census blockgroup. In this manner, we are shifting population from regions where there are no roads (where the probability of housing is low) to regions near roads (where we assume the probability of housing is higher). Distributing the population evenly across roads will still produce spatial errors, but less so than an areal average across the entire census polygon. Figure 2 shows the difference between datasets in which the population is distributed evenly across the polygon versus distributed to roads.

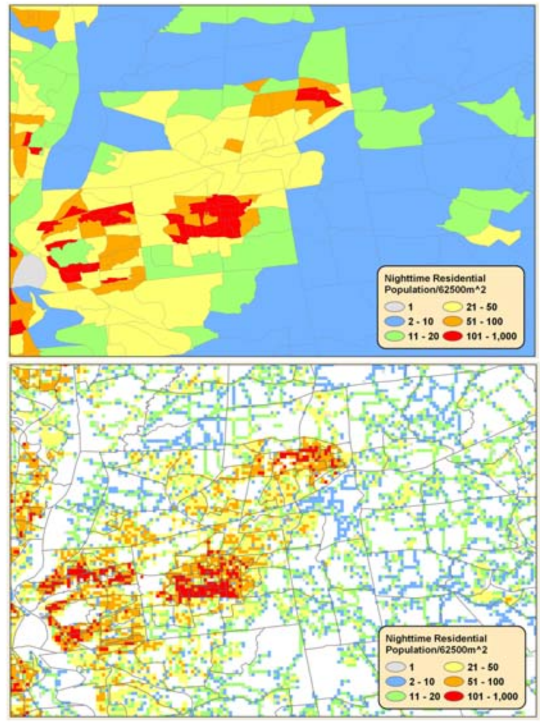

Figure 2. Comparison of an areal average of the Census Bureau residential population (top) versus the derived population attributed to roads (bottom).

In this research, the nighttime residential population grid was constructed using U.S. Census 2000 shortform population data coupled with the GDT street data. The vector based road data were converted to raster and then used to create a grid of location coefficients, which were used to disaggregate the census polygon data. Figure 3 shows an example of the residential population raster construction. The process begins with a vector map of 2000 Census blockgroups containing population counts. The GDT road data is then queried to define residential roads, i.e., those roads having a CFCC classification of A4*. Those residential road vectors are then converted to raster at a resolution of 25m, and the road cells in each census polygon are counted. The residential population location coefficient is then calculated according to equation 1:

$$p_{ri} = 1/r_{bg} \qquad (1)$$

where p_{ri} is the residential location coefficient for each grid cell i, and r_{bg} is the number of road grid cells per census blockgroup. The residential location coefficient represents the proportion of the total residential population in a blockgroup that may live in a given grid cell within that blockgroup. The raster map of location coefficients created using this method was used to disaggregate the total residential population in the blockgroup into each grid cell according to equation 2:

$$NRP_i = P_{bg} \cdot p_{ri} \qquad (2)$$

where NRP_i is nighttime residential population in each 25m grid cell i, p_{ri} is the nighttime residential location coefficient for each grid cell i, and P_{bg} is the residential population in each blockgroup. Following that step the 25m raster of nighttime residential population is aggregated to 250m for further calculations.

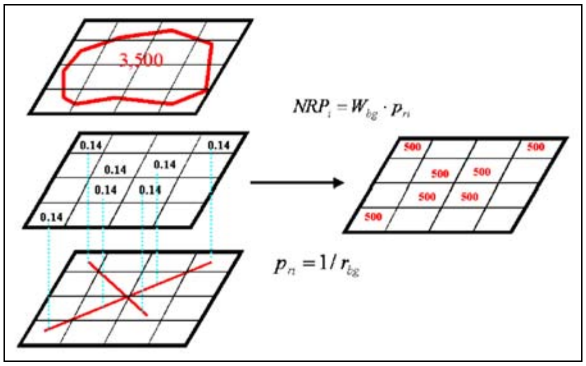

Figure 3. Example of nighttime population calculation. The roads (bottom left) are converted to raster and used to derive a location coefficient grid (middle left), which is subsequently used to spatially disaggregate the census count (top left) thereby producing the nighttime raster model (right).

3.3 Daytime Population

The daytime population model is composed of two components as shown in Figure 4. The first component is an estimate of the daytime worker population density. The second component is a raster of residential population that remains home during the day. In this case, we are assuming that non-working individuals remain in their residences during the day.

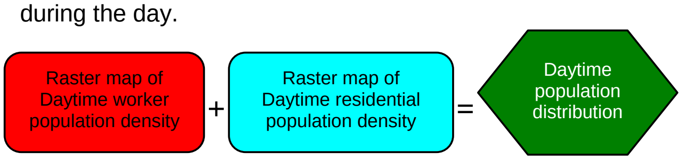

Figure 4: Derivation of the daytime population dataset.

The daytime worker population grid was constructed from two datasets: the 1999 State Business Directory and the 2000 U.S. Census "County to County Journey to Work" database. The daytime residential population was derived from our nighttime residential model and the Census "County to County Journey to Work" database. The SBD data was used to spatially disaggregate the number of workers in each county as defined by the Census Journey to Work data. The SBD includes three data fields that are useful in the placement of workers at facilities: 1) facility street address, 2) latitude-longitude, and 3) range of employees. The former two data types provide information on geolocation, while the latter provides information on the magnitude of the employment. Facilities in the SBD table for each state were geographically placed using either the ArcGIS geocoding tool with the Navtech Premium Street Data providing the street index or the latitude and longitude contained in the SBD for each record. Geocoding using the street address was the primary method for specifying facility location because there were no metadata available on the accuracy of the latitude and longitudes imbedded in the SBD. The accuracy of the placement of facilities was checked to assure each facility was placed in its correct 5-digit zip code area. Facilities that could not be placed due to poor address information and those that were placed in the incorrect zip code area were geographically placed again using the latitude and longitude imbedded in the SBD. These facilities were also checked against their zip code area, and those facilities that were placed in the wrong zip code were removed from the analysis. In this way, the geographic placement of facilities in the final vector file of businesses was accurate to at least the zip code area. A further improvement on the methodology would be to assess the spatial accuracy of the geolocations by using GPS to define the true geolocations of facilities. This task was not undertaken due to the expected expense of such an effort.

As noted earlier, the SBD data only provides a range of employees, while the Census Journey to Work database contains employee numbers but only at the county level. We used the higher spatial resolution SBD data to identify the locations of workers, and without any other information, used the midpoint of the employee range for the worker count. We then used the Census "County to County Journey to Work" database to scale the worker counts such that the total number of workers per county agrees with the Census database. Figure 5 shows an example of the steps used to create the daytime worker population raster.

Within the GIS, the SBD employee data were used to compute a grid of urban worker location coefficients that define the probability that an employee in the county works in a given grid cell. The worker location grid was calculated using equation 3:

$$p_{wi} = w_i \Big/ \sum_{i=1}^{n} w_i \qquad (3)$$

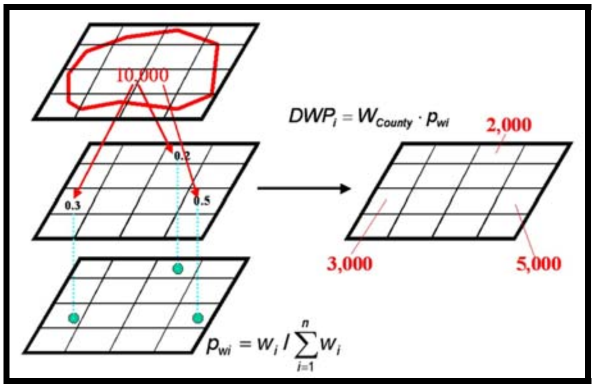

Figure 5. Example of daytime workplace population calculation. The businesses (bottom left) and their estimated workforce size were used to derive a location coefficient grid (middle left). The location coefficient grid was then used to spatially disaggregate the worker count derived for each county from the Census County to County Journey to Work data (top left) thereby producing the daytime workplace raster model (right).

where p_{wi} is the worker location coefficient for each grid cell i, and w_i is the estimated number of workers in each grid cell i in each county based on the SBD midpoint of the employee range. The worker location coefficient represents the proportion of the total workers in a county that may work in a given grid cell within that county. The raster map of location coefficients created using this method was used to disaggregate the census defined total number of workers in the county into each grid cell according to equation 4:

$$DWP_i = W_{County} \cdot p_{wi} \tag{4}$$

where DWP_i is workplace population in each 250m grid cell i, p_{wi} is the worker location coefficient for each grid cell i, and W_{County} is the total number of workers in the county.

The second step in the calculation of the daytime population is to define the daytime residential population distribution following the daily migration to workplaces. The daytime residential population was calculated using the same approach as the nighttime population dataset except the value to be disaggregated was the non-working population in each blockgroup, not the total population. The location coefficients were the same as those used for the nighttime residential dataset and the non-working residential population were disaggregated according to equation 5.

$$DRP_i = NW_{bg} \cdot p_{ri} \tag{5}$$

where DRP_i is daytime residential population in each 25m grid cell i, p_{ri} is the nighttime residential location coefficient for each grid cell i, and NW_{bg} is the non-working residential population in each blockgroup. Following that step the 25m raster of daytime residential population is aggregated to 250m for further calculations.

3.4 Indoor/Outdoor Fractions

Once the baseline daytime and nighttime population datasets were created, we defined the indoor and outdoor fractions of those populations using the NHAPS data. The NHAPS data contains codes representing each of the 99 possible locations in which a study participant could have been situated. Corresponding times and activity durations are also contained in the location information. The NHAPS activity data were separated in a relational database into indoor and outdoor activities at residences and workplaces. After establishing these categorical breakdowns, the resulting fractions were applied to the residential and workplace grids accordingly. Daytime residential, nighttime residential, and workplace outdoor fractions of population were calculated according to equations 6 - 8, respectively:

$$OF_{dayres} = \sum PM_{drout} \Big/ \sum PM_{dr} \tag{6}$$

$$OF_{niteres} = \sum PM_{nrout} \Big/ \sum PM_{nr} \tag{7}$$

$$OF_{work} = \sum PM_{wout} \Big/ \sum PM_{w} \tag{8}$$

where OF_{dayres} is the fraction of the population at residential areas that is outdoors during the day, PM_{drout} is the total person minutes of individuals spent outside at their residences during the day, PM_{dr} is the total person minutes of individuals spent at their residences during the day, $OF_{niteres}$ is the fraction of the population at residential areas that is outdoors during the night, PM_{nrout} is the total person minutes of individuals spent outside at their residences during the night, PM_{nr} is the total person minutes of individuals spent at their residences during the night, OF_{work} is the fraction of the population at workplaces that is outdoors, PM_{wout} is the total person minutes of individuals spent outside at their workplaces, and PM_w is the total person minutes of individuals spent at their workplaces. The resulting fractions are then used to disaggregate the daytime residential population, the daytime workplace population, and the nighttime residential population grids into indoor and outdoor components, which subsequently can be combined to define total daytime and nighttime indoor and outdoor populations.

Figure 6: LANL-derived nighttime (top) and daytime (bottom) population (aggregated to 1 km resolution) for the continental United States. Raw databases are at 250 m resolution and also include Hawaii.

4. Results

A day and night population database has been derived for the entire continental United States plus Hawaii at 250 m grid resolution (McPherson and Brown, 2003). Figure 6 displays the day and night population distribution for the continental U.S.A. at 1 km resolution. Figures 7-9 show comparisons of the nighttime and daytime population models for Seattle WA, Washington DC, and New York City NY, respectively. In each city, a migration from the surrounding residential/suburban areas towards the city center from night to day is shown.

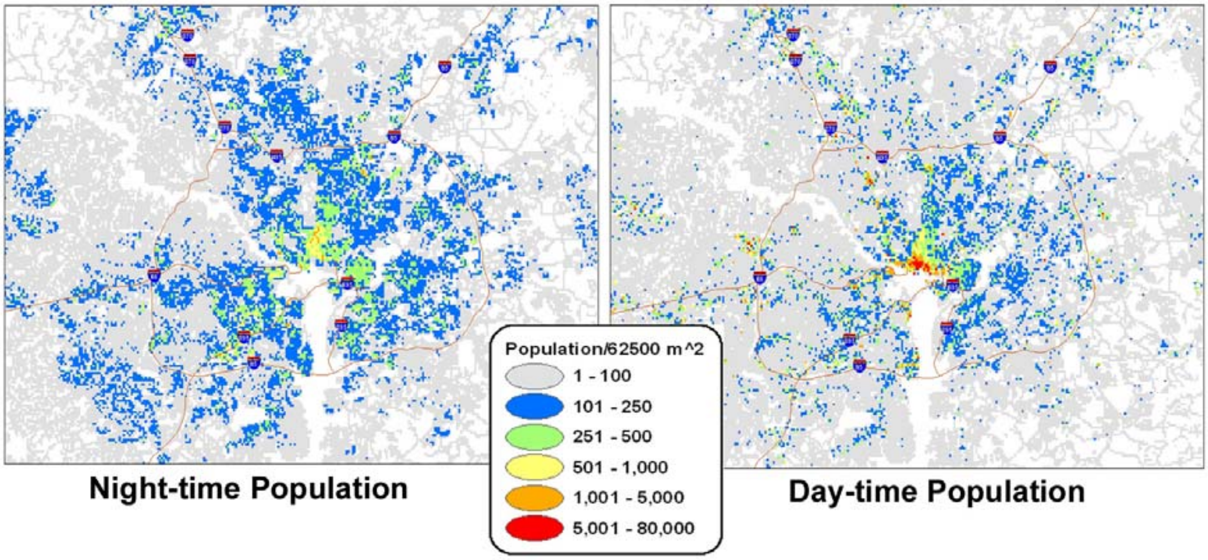

Figure 7. Nighttime population versus daytime population in Washington, DC.

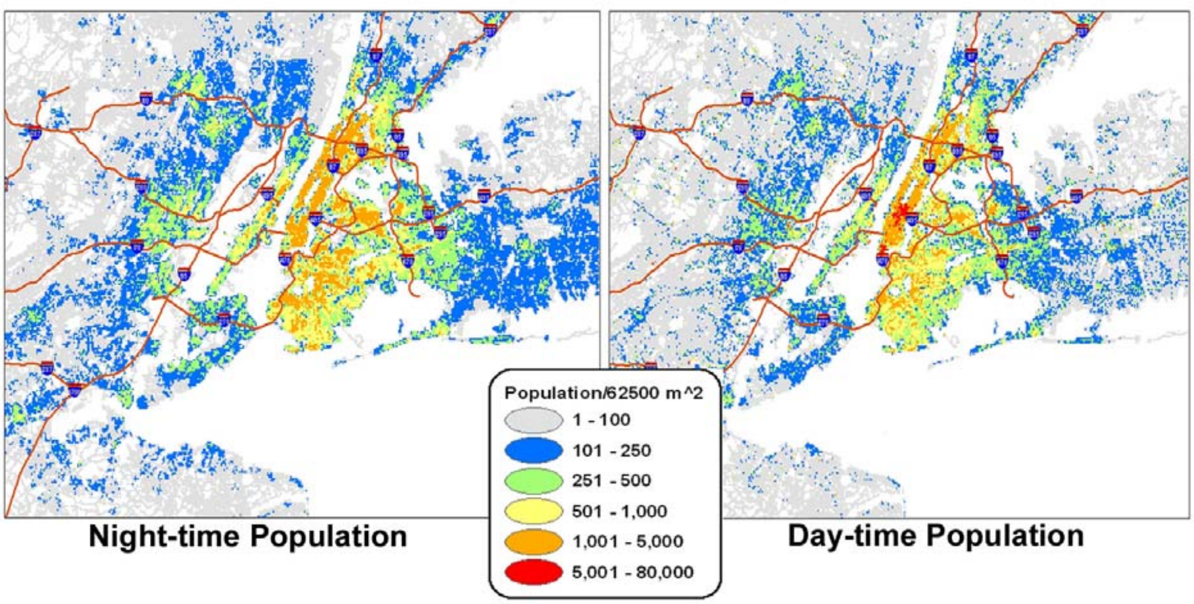

Figure 8. Nighttime population versus daytime population in New York City, NY.

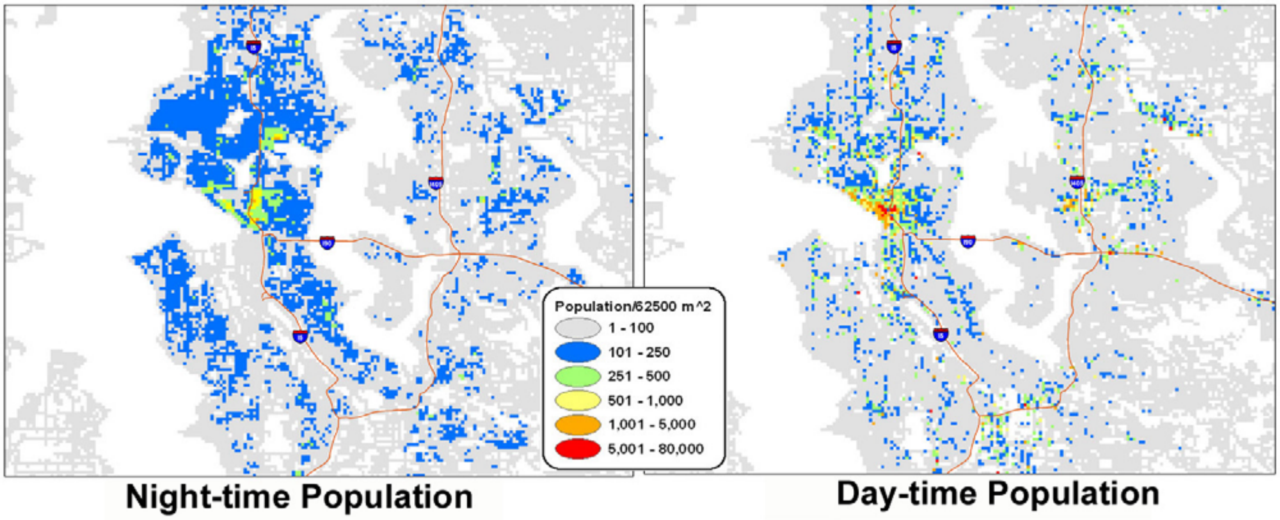

Figure 9. Nighttime population versus daytime population in Seattle, WA.

Figure 10 shows the difference between the day and night population databases of multiple cities in the downtown regions where the population difference between day and night may be greatest. In these select regions, the daytime population is 6.9 to 28.6 times greater than the nighttime population indicating significant variations do exist in the spatial distribution of populations throughout the day. This population variation can considerably alter exposure assessments in hazardous material release scenarios.

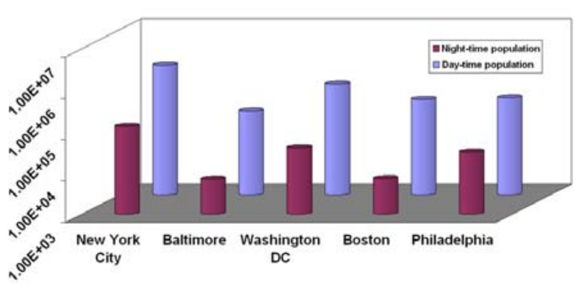

Figure 10. Daytime versus nighttime Population in downtown census tracts.

The indoor/outdoor fraction is another factor that needs to be considered in exposure assessments because of the shielding or protection provided to individuals within buildings during the passage of a toxic plume. For example, during the night-time hours from 9 pm – 6 am approximately 97.5% of the residential population are indoors and thus shielded in some way in the event of a nighttime airborne release. However, one should note that the full extent of the protection due to being indoors is a function of the permeability of the building in question, the ventilation system, and the physico-chemical characteristics of the toxic agent.

Figure 11 documents the temporal variation of indoor/outdoor population fraction at residential locations computed using our methodology.

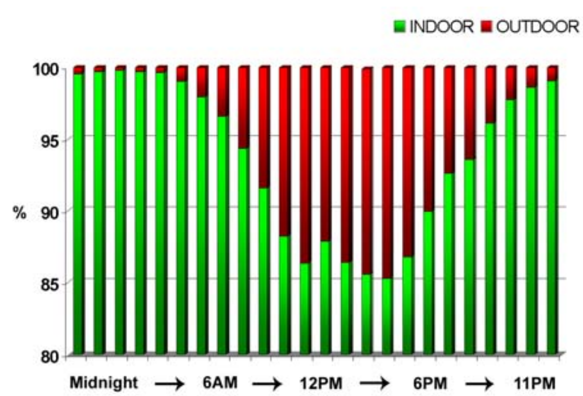

Figure 11. Indoor/Outdoor fluctuation within residential areas.

The graph shows that during the daytime, about 15% of the residential population is outdoors. During the night, this number shrinks to about 2 to 3%. In our dataset these hourly breakdowns of indoor/outdoor fractions were aggregated to a 12 hour time step similar to daytime and nighttime (i.e., 6 am to 6 pm and 6 pm tp 6 am) and combined with the daytime and nighttime population datasets to create a spatial estimate of indoor and outdoor populations**.** Figure 12 shows an example of our indoor and outdoor population datasets for the daytime in Houston TX. Although outdoor fractions are greatest during the day, the vast majority of the population is indoors.

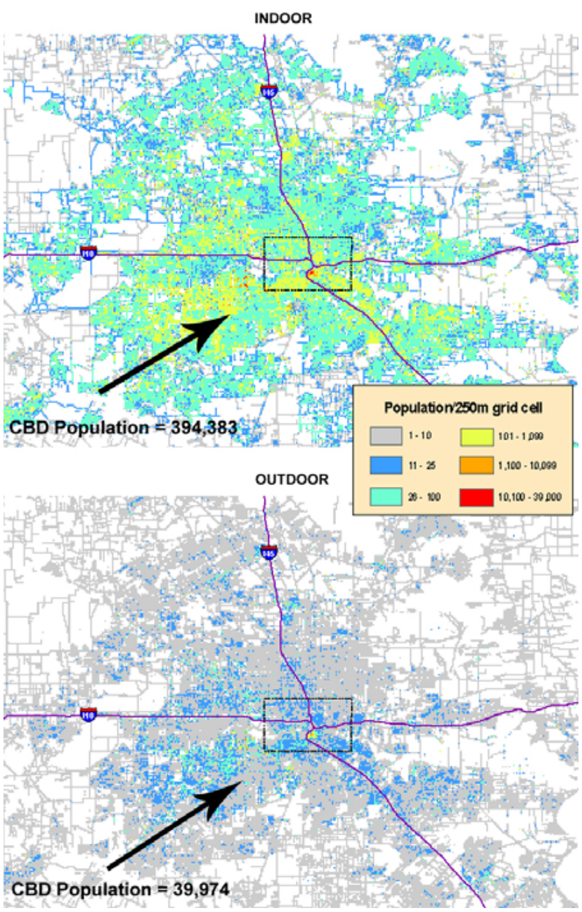

Figure 12. Indoor and outdoor populations in the Houston Central Business District (CBD)

5. Houston Case Study

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The importance of accounting for the daytime indoor/outdoor distribution of urban populations is illustrated in a case study of a hypothetical chemical spill in Houston TX. Figure 13 shows the estimated number of affected people within a plume resulting from a hypothetical daytime industrial accident using the daytime and nighttime population datasets. For these plume dispersion simulations, all meteorological conditions and plume dispersal parameters were held constant to facilitate direct comparison of daytime and nighttime population databases. In this scenario, the material release occurred during the day near the Houston ship channel with moderate winds from the Southeast. The simulated plume traveled northwest towards downtown Houston. In this daytime release case, the number of affected individuals within the plume is a factor of 2 greater when using the more appropriate daytime population database as opposed to the nighttime population database. .

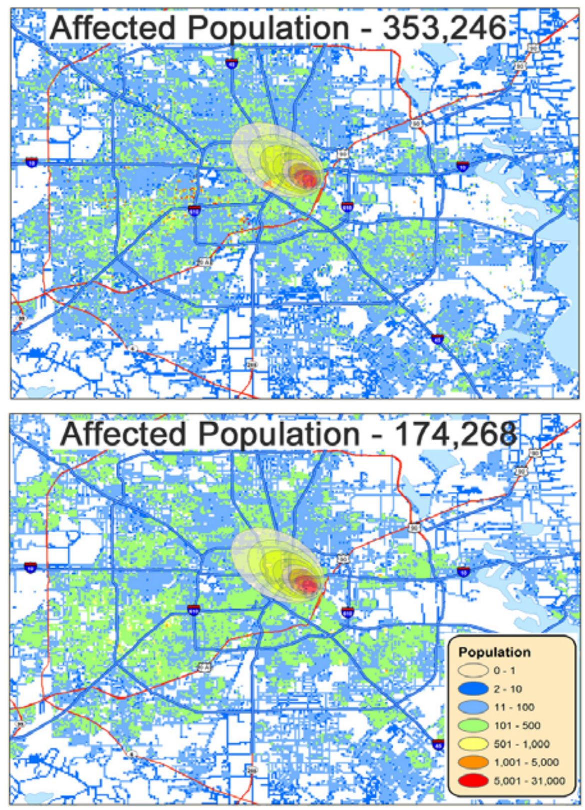

Figure 13. Affected population in Houston during a hypothetical daytime industrial accident. Simulated daytime plume dosage contours overlaid onto population density. Tile on top shows the estimated population affected by the plume using the more appropriate daytime population dataset. The bottom tile shows the estimated population affected using the less appropriate nighttime population dataset.

Furthermore, when considering the indoor and outdoor status of the population, the potential difference in exposed population is even more significant. Table 2 lists the affected population that is indoors and outdoors within the plume during the day and night. The number of individuals that may be expected to be fully exposed without any sort of protection in the immediate time period after the material release (i.e., the people outdoors) is an order of magnitude less at night. These differences in the magnitude of the affected population could impact planning for post-release emergency response and hospital triage

Table 2. Indoor/outdoor components of the population within simulated plume.

Time	Indoor Population	Outdoor Population
Day	315,060	38,186
Night	170,657	3,611

6. Progress to Date/Future Efforts

As shown in Figure 6, daytime and nighttime populations have been constructed for all of the continental United States and Hawaii. This area covers 99.8% of the U.S. population. Although daytime and nighttime population datasets have been constructed for all states, these results are preliminary. The results generated using the method documented within this report are representative of maximum daytime workplace population and maximum nighttime residential population. Although these peaks represent an improved estimate of the temporal distribution of urban populations over standard nighttime population databases, there are many potential improvements that could further increase the value of the dataset. For example, greater specificity of both the temporal and spatial distribution of population will allow for better risk assessments in hazardous material release scenarios. Potential improvements to the dataset include, but are not limited to, the following:

1. Determination of the spatial and temporal distribution of populations commuting between work and home, i.e., the traffic component of the population.
2. Determination of the spatial and temporal distribution of populations at educational facilities.
3. Determination of the spatial and temporal distribution of populations in retail zones.

7. Summary

In order to address the potential shortcomings in exposure assessments of hazardous material releases, six population datasets were constructed to more accurately represent the temporal and spatial distributions of populations under hazardous material plumes. Exposed populations are difficult to define because population distributions shift throughout the day according to the work, shopping and mobility habits of urban citizens. Most available population datasets were constructed for purposes other than exposure assessments and often have no temporal component and a limited spatial component. These population datasets are based typically on residential units such as households or families and are often geographically constructed based on sampling design instead of spatial accuracy. Residence-based population datasets may be useful in exposure assessments if analysts can assume the majority of the population are at their residences. This assumption may be valid at night, but during the day it may be significantly inaccurate. Therefore, the use of these population data in exposure assessments may misrepresent the actual population exposed to the material in question.

In this research, we created six databases that account for daily population migrations. Raster based models of nighttime and daytime population, as well as the indoor and outdoor components of those populations, were constructed in a GIS with a 250-meter resolution. The population datasets cover the continental United States and Hawaii and represent 99.8% of the U.S. population. To date, indoor/outoor fractions have been derived for California, Illinois, Indiana, Massachusetts, New Mexico, New York, South Carolina and Texas. The raster format was used to facilitate the derivation of the spatial models and to improve the ease of use of the datasets in exposure assessments. The majority of urban dispersion models are grid based and the construction of the population models as grids may hasten their use in those codes.

The value of the models in exposure assessments is significant. Considerable differences were found between the derived daytime and nighttime indoor/outdoor population datasets. Daytime populations in downtown census tracts were found to be 6.9 – 28.6 times greater than the nighttime populations in the same census tracts. These differences could have profound impacts on exposure assessments and emergency management decisions during hazardous material release events.

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