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DATA DRIVEN APPROACH FOR HIGH RESOLUTION POPULATION DISTRIBUTION AND DYNAMICS MODELS

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ABSTRACT

High resolution population distribution data are vital for successfully addressing critical issues ranging from energy and socio-environmental research to public health to human security. Commonly available population data from Census is constrained both in space and time and does not capture population dynamics as functions of space and time. This imposes a significant limitation on the fidelity of event-based simulation models with sensitive space-time resolution. This paper describes ongoing development of high-resolution population distribution and dynamics models, at Oak Ridge National Laboratory, through spatial data integration and modeling with behavioral or activity-based mobility datasets for representing temporal dynamics of population. The model is resolved at 1 km resolution globally and describes the U.S. population for nighttime and daytime at 90m. Integration of such population data provides the opportunity to develop simulations and applications in critical infrastructure management from local to global scales.

1 INTRODUCTION

High resolution population distribution data are essential for successfully addressing critical issues ranging from socio-environmental research to public health to homeland security (Dobson et al. 2000; Bhaduri et al. 2002, 2005, 2007; Chen 2002; Hay et al. 2005; Sutton et al. 2001). Typically population data are reported by administrative or accounting units. For example, in the U.S., the source for population data is the U.S. Census Bureau, which reports population counts by census blocks (smallest polygonal unit), block groups (aggregated blocks), and tracts (aggregated block groups).

From a spatial perspective, Census data are limited by Census accounting units (such as blocks), and there is often great uncertainty about the spatial distribution of residents within those accounting units. This is particularly apparent in suburban and rural areas, where the population is dispersed to a greater degree than urban areas. At any resolution, a uniform population distribution is assumed and the population figures and demographic characteristics are typically associated with block (polygon) centroids. In geographic analyses these points are considered representative of the population for census polygons and represent key initial conditions for models. For example, calculation of travel time to health care providers considers these centroids as the starting points for travel. For exposure and risk analyses, these centroids often serve as "receptor" points for calculating exposure or dosage from any dispersed agent. Traditional spatial modeling approaches commonly include intersection of census data with

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buffers of influence to quantify target population, using either inclusion-exclusion (of the centroids) or area-weighted population estimation methods. However, it is well understood that uniform population distribution is the weakest assumption and by considering census polygon centroids as representative of population, all analytical approaches are very likely to overestimate or underestimate the analytical results.

From a temporal perspective, Census counts represent "residential" or "nighttime" population and its usage in a daytime event simulation is illogical. Because of this uncertainty, there is significant potential to misclassify people with respect to their location from, for example pollution sources, and consequently it becomes challenging to determine if certain sub-populations are actually more likely than others to get differential environmental exposure.

2 BACKGROUND

2.1 Spatial Decomposition of Census Data

Decomposition of population distribution estimates has been recognized as a key issue in spatial research and applications. A number of interpolation and decomposition methods have been developed to address this issue with census (polygonal) population data; namely area-weighted interpolation, pycnophylactic interpolation, dasymetric mapping, and various smart interpolation techniques. Areal weighted interpolation is the simplest of the methods where a regular grid is intersected with the Census polygon and each grid cell is assigned a value based on the proportion of the polygon contained in each cell (Goodchild and Lam 1980, Goodchild, Anselin, and Deichmann 1993, Mennis 2003). This method implies an assumption of uniform distribution of population which is not a realistic solution for decomposition of population data. Pycnophylactic interpolation extends areal weighting methodology by applying a smoothing function to the raster cell values, with the weighted average of its nearest neighbors, iteratively while preserving the total population count of the polygon (Tobler1979). This method creates a continuous surface which contradicts the obvious discontinuous nature of population distribution. Dasymetric modeling is analogous to areal interpolation but uses ancillary spatial data to aid in the interpolation process. The ancillary spatial data is at a finer spatial resolution and the variability in its values enables an asymmetric allocation of population values. Land cover/land use is the best example in this respect where different land cover or land use categories for each cell can be used as weighting functions for population distribution such that urban areas will have a higher weight than forested areas (Figure 1) (Mennis 2003, Wright 1936, Langford and Unwin 1994).

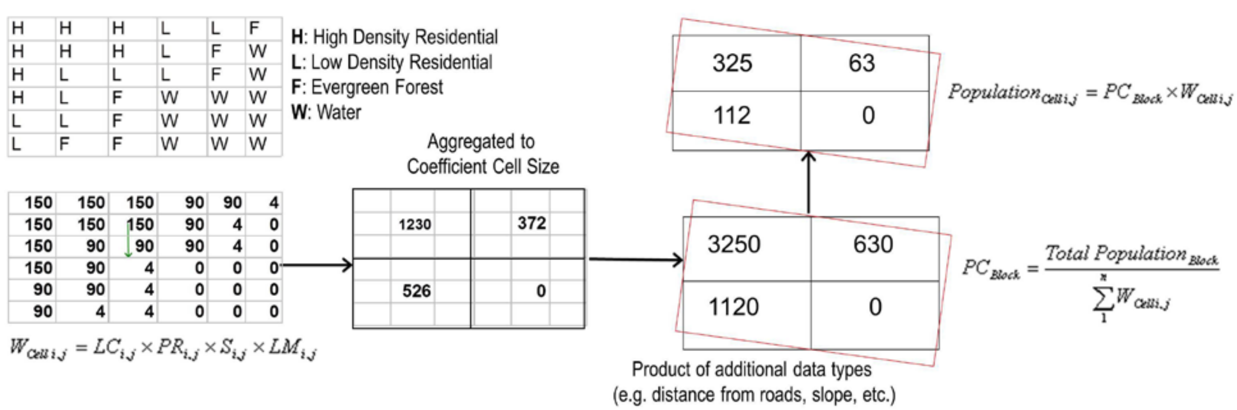

Figure 1. A schematic explanation of dasymetric interpolation technique.

Smart interpolation, in principle, is a multidimensional version of dasymetric model where the allocation refinement comes from more than one ancillary data sources which are at a finer resolution than the population polygon (Langford and Unwin 1994, Cohen and Small 1998). Utility of such interpolation techniques at local scales are well documented.

2.2 Temporal Decomposition of Population Data

Modern censuses are designed for medium to long term planning purposes and account for nighttime residential population. Temporal scales of these planning activities require a general geographic assessment of population described through their residential locations, and such assessments are adequate to address such planning processes. In the U.S., block level temporal dynamics are captured at decadal scale while county level dynamics are assessed yearly. Not much attention has been paid to the formal assessment of population dynamics at finer temporal scales ranging from seasonal to monthly to daily and hourly. Movement of population during a day results directly from people traveling to their locations of daytime activities (employment, business, educational institutions, and recreational locations) away from their residences [3]. The patterns of such population displacements depend on the relative geographic distribution of residential and business areas. In most modern societies, these two activity locations are distinctly separated in space, and employment or business locations contain fewer residences compared to businesses. Consequently, a large number of people move into these areas while only a few leave resulting in a substantial swelling in the daytime population of that area. Motivation to formalize the concept of non-residential and daytime population distribution roots predominantly in two areas. First, it has been well-perceived that understanding of the daytime population distribution provides a very competitive economic advantage as businesses are enabled to target specific consumer bases depending on their locations and convenience of access during the majority of the 24-hour period when people are out of their residences. In recent years, a stronger requirement for understanding daytime population has emerged from the emergency preparedness and response community to assess the at-risk population from the threats of technological and natural disasters, and deliberate attacks on human lives such as terrorist events.

Development of daytime population distribution models and databases is significantly more challenging as it requires further integration and modeling of activity based datasets into the residential population distribution model. In 2004, the U.S. Census Bureau released the following three daytime population distribution data tables based on the 2000 Census (U.S. Census Bureau 2000):

1. Leading Places on Percent Change in Daytime Population, by Size (202 highly populated cities)
2. The United States, States, Counties, Puerto Rico and Municipalities
3. Selected Places by State (6524 communities)

However, these data sets only take into account commuting worker population in an area. The best spatial resolution of these data is still at the community level (small cities) and thus is appropriate for general purpose planning.

3 ESTIMATION OF HIGH RESOLUTION POPULATION DISTRIBUTION

3.1 LandScan: A Data Driven Approach

Geospatial data and models offer novel approaches to decompose aggregated Census data to finer spatial and temporal units. Our approach, known as LandScan, involves multi-variable fusion of physical and social data that may or may not be in explicitly spatial formats to model and visualize relevant characteristics of human behavior, natural process evolution, and landscape changes over space and time. This has resulted in the finest global population distribution model and database ever produced using worldwide imagery and other spatial data (Dobson et al. 2003; Bhaduri et al. 2002).

The LandScan population distribution model involves collection of the best available census counts (usually at sub-province level) for each country and four primary geospatial input datasets, namely land cover, land use, roads, slope, and other physiographic features that are key indicators of population distribution. Dasymetric modeling uses ancillary spatial data at a finer spatial resolution to augment the interpolation process. The spatial discontinuity and attribute variability in the ancillary data allows an asymmetric and discontinuous allocation of population (Eicher and Brewer, 2001; Mennis, 2003). A number of ancillary databases, such as land cover and land use, roads, cultural landmarks, at spatial resolutions finer than Census blocks are spatially integrated in this allocation modeling approach to distribute the total number of population reported for a spatial enumeration unit, for example, a Census block. Land cover/land use is one of the most relevant example in this respect (Monmonier and Schnell 1984; Reibel and Agrawal 2006) where different land cover or land use categories for each cell can be used as weighting functions for population distribution. For example, urban areas will have a higher weight than forested areas and hence higher population. LandScan Global, at 30 arc-seconds or approximately 1 km cell size, is derived through advanced spatial data integration. However, this model represents an ambient population or an average distribution over a 24-hour period and hence residential population is underestimated and some population is assessed at likely locations of daytime activities such as roads and commercial areas.

We have further developed this approach where a large number of disparate and misaligned spatial data sets can be spatiotemporally correlated and integrated in an activity-based modeling (ABM) framework to understand, model, and visualize the dynamics of population (Bhaduri 2007; Bhaduri et al. 2007). LandScan USA represents a model and database for the U.S. which separately describes population distribution at 90m spatial resolution for nighttime (residential) as well as daytime scenarios (Figure 2). Locating daytime populations requires not only census data, but also other socio-economic data including places of work, journey to work, and other mobility factors such as daytime business and cultural attractions/populated places datasets.

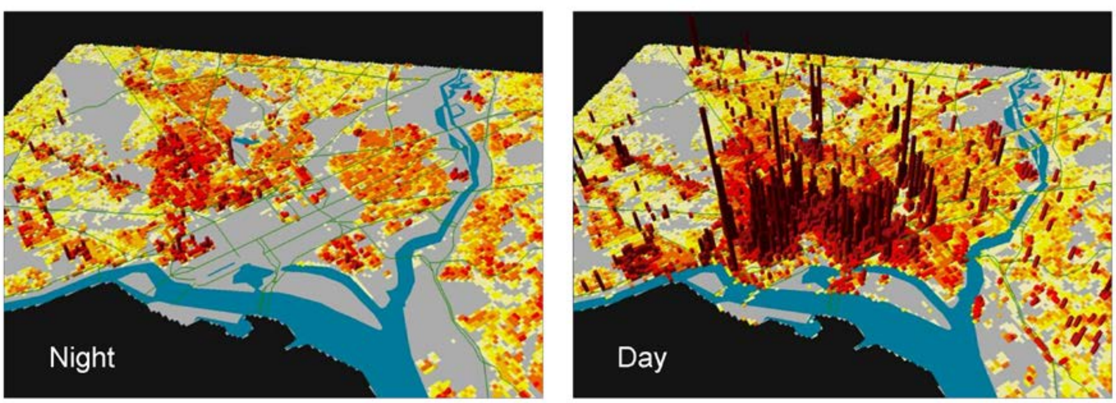

Figure 2: Diurnal dynamics of population distributions in Washington, DC, USA are modeled with LandScan USA high resolution population data.

An important aspect of daytime population distribution is the geospatial scale at which it is estimated. Theoretically, the finest spatial resolution achievable through the map algebra technique described above is directly tied to the finest scale of the available input data. For example, the U.S. Census Bureau collects worker commuting data at the census tract level and reports national daytime population distribution at the county level. It also reports estimates of daytime population for key cities in each state. Similar city-level estimates of daytime population from government and commercial sources are available for Japan (Japanese Statistics Bureau 2000), Canada, and the U.S. All these data sets appear to be heavily focused on worker population movement during the day and the data is presented through vector data models (points and polygons). For example, daytime population fluxes are restricted to individual county and city boundary polygons. Some commercial databases represent individual activity locations as points which potentially offer high spatial accuracy, but mostly account for worker population at individual business locations. In reality, the datasets necessary to comprehensively estimate daytime population exist in the forms of points and polygons which makes it challenging to create a high resolution population distribution through simple map algebra analysis. It requires integration of disparate spatial data and advanced geospatial modeling where the spatial model enables decomposition of the input data into finer spatial resolutions and represented through a uniform raster or gridded dataset. Development of daytime population distribution has been discussed in detail by Bhaduri (2008).

4 ASSESSING POPULATION DYNAMICS AT HIGH TEMPORAL RESOLUTION

Beyond an average daytime representation, as with the case of LandScan USA, there is considerable interest in understanding time variant population distributions at finer temporal scales ranging from minutes to hours. Facility or land use based approach in LandScan USA allocates population strictly within critical infrastructures and activity structures and fails to account for mobile population or population in transition along the transportation infrastructures. A couple of approaches are prevalent in simulating population dynamics at finer temporal scales.

4.1 Interpolation and Occupancy Based Approach

Interpolation based methodology for visualizing and analyzing diurnal population change for metropolitan areas has been developed as early as the early 1980s (Goodchild and Janelle 1984). Inherently, enhancing the temporal resolution is achieved through a high-resolution spatial representation of human activities, which in turn requires exact locations of facilities or critical infrastructures coupled with representative representation of human usage of those facilities. Kobayashi et al. (2009) utilized areal interpolation within a geographic information system to create twenty-four (one per hour) population surfaces for the larger metropolitan area of Salt Lake County, Utah from population data at the transportation analysis zone level in fifteen-minute increments available from the U.S. Department of Transportation. The resulting surfaces represent diurnal population change for an average workday and are easily combined to produce an animation that illustrates population dynamics throughout the day. In this context, we utilize the concept of "facility occupancy curves" that represent the number of people occupying those facilities over time (Figure 3).

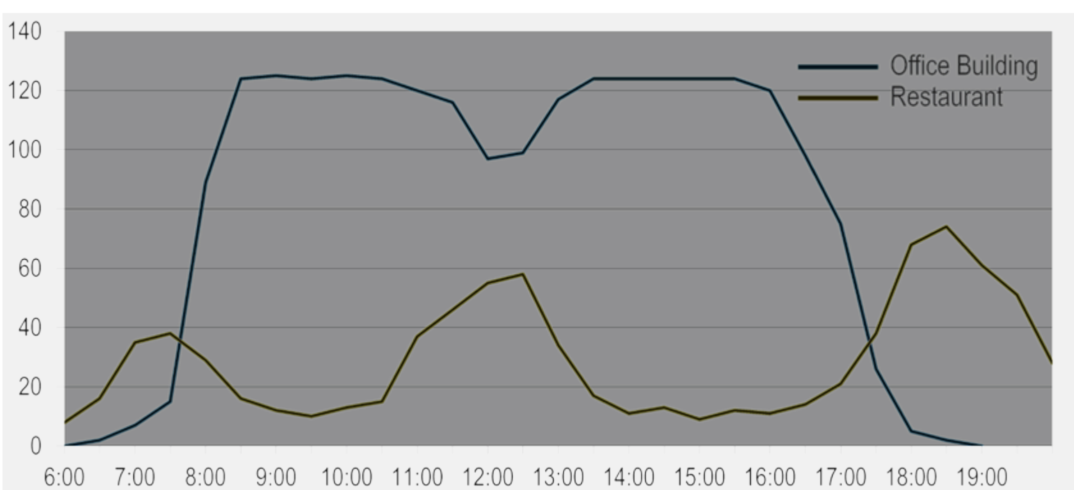

Figure 3. Conceptual representation of occupancy curves for two different activity locations or facilities.

Utilizing a time-driven simulation approach, the state of every cell is recomputed at regular intervals of time. This is done by sweeping through the cell space and applying each cell's transition rules. In the case of LandScan USA, baseline nighttime population of every 90m cell could be extrapolated with a population buildup function and reaching the maximum value during the daytime, followed by a depopulation function that brings the population back to the nighttime baseline level.

4.2 Transportation Simulation Based Approach

Transportation modeling and simulation approaches can be utilized to describe and visualize movement of population along transportation networks. These approaches also represent the general methodological principles of moving vehicles along transportation networks. In particular, micro-simulations of traffic, vehicular and pedestrian, can generate very fine temporal resolution population distribution data. A number of existing transportation simulation models characterize the interaction between the human dynamics and transportation infrastructure, and require the integration of three distinct components, namely, data, models, and computation. These include detailed physical models of transportation engineering, such as are found in CORSIM (U.S. DOT 1997), TRANSIMS (Smith et al. 1995, Fisher 2000), VISSIM (Bloomberg and Dale 2000), and OREMS (Bhaduri, Liu, and Franzese 2006, Franzese and Han 2002). LandScan data has been successfully integrated with transportation micro-simulations, via a vehicle occupancy ratio, to realistically emulate movement of population. Commuting patterns for individual demographic groups (such as school children) can be simulated in finer temporal resolutions to assess potential impact from atmospheric pollution to commuting school children (Shankar et al. 2005; Xue et al. 2008). A popular scenario is evacuation modeling which can be considered as a special situation where the movement of people is expected to have certain specific directionality since the objective is to move population residing inside a geographic area across and outside its boundary (Bhaduri et al. 2009).

5 LIMITATIONS AND FUTURE RESEARCH

High resolution, data driven development of population distribution and dynamics models across geographic scales is an emerging frontier for geospatial modeling and simulation. High resolution population databases, such as LandScan USA, are imminently expected to enhance the current fidelity of spatial analysis, modeling, and decision support activities in application domains across the areas of homeland security, emergency preparedness and response, socio-environmental studies, and public health, and consequently allow evaluation of existing policy. Qualitative and quantitative verification and validation of the modeling parameters and quality assessment analysis demonstrate a high degree of precision and locational accuracy for the LandScan USA model and database. As discussed earlier, relative distribution of the population in and around activity locations are rather subjective and based on a number of logical assumptions made by the analysts. This clearly introduces some level of subjective variability and uncertainty to the reported population for individual cells. Currently the LandScan USA database does not provide any measure of such variability or uncertainty and we acknowledge this to be a critical issue. Geospatial and temporal dynamics of population are complex social processes. Consequently, effective characterization of such population dynamics requires development of high resolution spatial and temporal models that adequately capture social complexity and its influence on human movement patterns. As the resolution of available spatial data increases (for example parcel level data are now being collected and distributed by most state and local governments), it is logically possible to increase the resolution of population distribution models to the corresponding resolution. Model validation, however, is the most burdensome, but also the most critical and least explored, aspect of population dynamics modeling. Lack of consistent data about the movement of population at a suitable resolution in both time and space has been the single greatest barrier to validation, but recent advances in technology are poised to overcome this problem. Location services have become ubiquitous in mobile phones, personal digital assistants, and in vehicles themselves. This data, if it were available to the community of modelers, could be used routinely for validation in the context of typical, day-to-day population flow. Over a period of several years, this validation activity and the consequent refinement of models will significantly reduce the discrepancies in the outcomes of different simulation tools.

For interpolation based approaches, the mathematical nature of these facility occupancy functions (shape of these occupancy curves) could be theoretically modeled, however, developing them empirically from available data is desirable but requires a significant volume of observation data. Increasing availability of observation-based geographic data along with volunteered geographic information through social media platforms, such as Twitter, presents an opportunity for empirical development and characterization of population occupancy curves. Research efforts are underway to explore optimal approaches for utilizing conventional observation and measurement data, and unconventional sources (social media) for assessing and quantifying uncertainty in such population distribution databases to be reported in the future.

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