Spatial Estimation of Populations at Risk from Radiological Dispersion Device Terrorism Incidents – 8408

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ABSTRACT

Delineation of the location and size of the population potentially at risk of exposure to ionizing radiation is one of the key analytical challenges in estimating accurately the severity of the potential health effects associated with a radiological terrorism incident. Regardless of spatial scale, the geographical units for which population data commonly are collected rarely coincide with the geographical scale necessary for effective incident management and medical response. This paper identifies major government and commercial open sources of U.S. population data and presents a GIS-based approach for allocating publicly available population data, including age distributions, to geographical units appropriate for planning and implementing incident management and medical response strategies.

INTRODUCTION

Predicting the likely severity of a terrorism event in terms of its impact on human health, especially the number and type of fatalities and injuries likely to occur, is one of the key challenges in designing and implementing measures to prevent or minimize adverse consequences [1]. Moreover, because clinical manifestations of psychological effects also may occur subsequent to an incident [2-4], this also can aid in identifying target areas for developing effective post-event mental health interventions. This is particularly important in order to gauge the possible health impact of non-conventional terrorism incidents, especially the intentional release of biological pathogens or low doses of ionizing radiation by a low-yield nuclear device or a radiation dispersion device (RDD) commonly called a dirty bomb. In part, this is due to the time lag that typically occurs between the actual release and the onset of physiological symptoms unlike events involving explosives where the physical effects of blunt trauma are readily apparent or chemical attacks in which evidence of exposure in the form of fatalities and/or individuals presenting clinically for treatment tends to be fairly rapid [5-7]. And, although this problem is lessened with chemical exposures because effects are likely to manifest instantaneously or within a few hours, it clearly is problematic with suspected biological events where clinical presentation of effects can be delayed for days or even weeks.

With exposure to radiation, clinical manifestations of physiological effects are contingent on the absorbed dose of radiation. For many of the victims, the dose will be below the threshold for acute radiation syndrome (ARS) – also commonly referred to as radiation sickness – of whole-body or significant partial-body irradiation > 1 Gy delivered at a relatively high dose rate but still produce exposure to ionizing radiation. With respect to nuclear terrorism, the detonation of low-yield nuclear weapons (≤ 20KT), a matter of increasing concern because of the global risk of terrorism, could produce expose to low-doses of ionizing radiation raising the possibility of developing cancer with its

corresponding physiological and psychological effects. Because clinical manifestations are contingent on the absorbed dose of radiation, this may prove to be the determining factor in selecting appropriate medical responses to low-doses of ionizing radiation [8-11]. The degree of difficulty is further exacerbated with radiological events involving low levels of ionizing radiation typical of 'dirty bomb' scenarios [12]. Additionally, various tissues differ as to their response to ionizing radiation underscoring the importance of establishing measurable endpoints linked to dose. As a result, making extrapolations to dose and biological effects based on studies of high-dose populations such as the 1945 Hiroshima and Nagasaki atomic bomb survivors is a difficult and complex process as demonstrated by the ongoing series of Biological Effects of Ionizing Radiation (BEIR) reports prepared by the National Academy of Sciences [13-14]. Such lags between exposure and biological effects, especially with low-dose ionizing radiation associated with the detonation of a RDD, underscore the importance of being able to delineate well the population to monitor prior to the onset of physiological effects. As a result, accomplishing this objective will support effective triage and medical management of casualties based on rapid, non-invasive estimation of radiation exposure [15-19].

Because severity expressed as mortality and morbidity partially is contingent on the pool of potential targets, accurate population data – including age distributions given the unique vulnerabilities of infants and the elderly – are essential for analysis designed to support decision-making since the number of adverse outcomes for those types of events is a function of the number of people exposed [20]. Such information, when coupled with dose and exposure estimates, provides the underlying basis for developing risk-based response measures. Consequently, access to good data about the size and spatial distribution of the potential population at risk to exposure is critical. Unfortunately, real world data on the distribution of populations over time and across space are often very fragmentary, incomplete, outdated, or entirely lacking. Delineating the size and spatial distribution of populations potentially at risk also is made complex because, during the course of a given day, people move from place to place as well as from indoors to outdoors. These factors make it difficult to relate population distributions to specific locations on a temporal-spatial basis. As a result, delineating the number of people potentially at risk (i.e., population) due to a terrorist attack involving non-conventional weapons can be difficult. This forces analysts and decision makers to rely on estimates of population distributions. This paper presents a GIS-based approach for addressing the problem of allocating readily available, open source population data to geographical units appropriate for planning and implementing incident management and medical response strategies.

APPROACH

Generating credible estimates of the number of people and their spatial distribution across geographical boundaries relevant to a non-conventional terrorism event such as the detonation of a RDD requires analysts to solve two interrelated problems. First, population counts arrayed on a defined spatial basis such as census blocks or zip codes need to be available. Second, a defensible basis for reliably updating those counts and allocating them spatially to relevant geographical units that are defined by the dynamics of the event has to be used. In essence, one faces the task of interpolating data often collected at one level of resolution as well as a single point in time to either the same or

different spatial scales in order to match the area affected by the event (see Figure 1). Geographical information systems (GIS) coupled with computational algorithms provide a convenient approach for addressing these problems. The following sections summarize the elements of a GIS-based approach for using open source population data to estimate the size and location of populations potentially exposed to ionizing radiation released by RDDs during terrorism incidents.

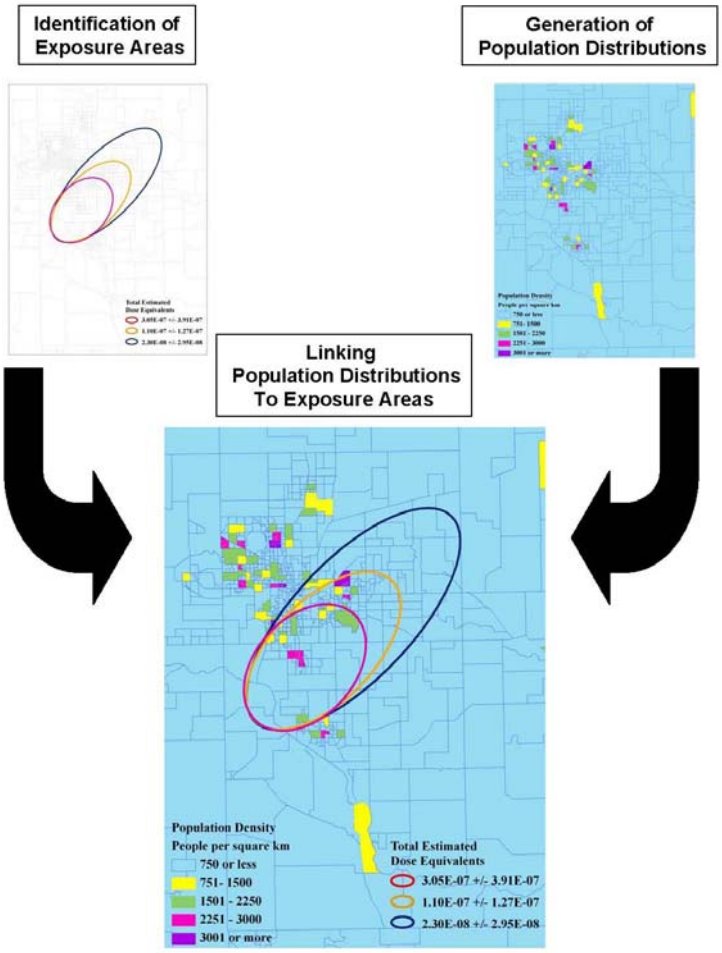


Figure 1. Schematic of the Process for Spatial Interpolation of Population Data

Open Source Data for Estimating Populations at Risk

A wide array of open source data for the U.S. civilian population are available from government or commercial providers (see Table 1). However, those data typically are not collected specifically to support exposure estimation and risk assessment. Instead, various computational algorithms have to be applied to those data to derive population estimates which are allocated on a daytime versus night-time basis to specific geographical units relevant to planning and implementing incident management and medical response strategies [21-24]. As a result, the quality of estimates of populations at risk is contingent

on the comprehensiveness, frequency of collection, time frame (daytime vs. night-time), and spatial scale (aggregate geographic units with discrete boundaries) of the underlying dataset used to identify populations of interest [25].

Table 1. Major Government and Commercial Open Sources of U.S. Population Data

Data Source	Comprehensiveness	Frequency	Time Frame (Day/Night)	Spatial Scale
U.S. Decennial Census	Complete count of US population by households	Once every 10 years	Night-time	Block (Block group level for much of the demographic information)
American Community Survey	Sample estimate of population characteristics for geographic areas with populations ≥ 65,000 by U.S. Census Bureau	Annually starting in 2010 (tracts every 3 years; block groups every 5 years)	Night-time	County subdivisions
Longitudinal Employer-Household Dynamics Program	Limited to 25 states; combines state administrative data with survey data from U.S. Census Bureau	Quarterly	Daytime	Varies from county down to WIA
Census Transportation Planning Package	Place of work and residence; worker-flows by county	Once every 10 years	Daytime	Varies from traffic analysis zone (Parts 1 & 2) to block group (Part 3)
infoUSA	210 million US consumers and 14 million US businesses	Monthly	daytime	Zip code plus 4 (< zip code)

Each of the major sources of readily available data has limitations, especially in terms of trading off high spatial resolution for high temporal accuracy. Moreover, each provides either daytime or night-time counts so computational techniques have to be employed to derive data for both timeframes. For example, although the current version of the decennial census is the most comprehensive, it is only conducted once every 10 years and reflects residence not place of work aggregated within political jurisdictions to various levels of spatial resolution. Currently, the decennial census has the highest level of spatial resolution for open source demographic data (i.e., block). Using a combination of the "short form" questionnaire completed by five out of every six households in the U.S. and the "long form" questionnaire completed by the remaining one of six households, the decennial census provides a "100% count" of the U.S. population (i.e., enumeration). The long form, unlike the short form, is based on statistical sampling and provides additional demographic information that can be used to characterize population attributes such as income, housing tenure, employment, transportation to work, education, and migration patterns.

Figure 2 illustrates the spatial relationships between the geographical entities. The block level is the smallest spatial scale for which population characteristics are available and is the scale at which short form data are collected. Blocks do not have a constant area (i.e., non-uniform polygons), and their size depends on the population count within the block. The number of households is not fixed either and is partially dependent on the ease of data collection. For example, households may be clustered within a block (i.e., apartments, condos, subdivisions with small lots) so that blocks containing clusters of households normally have more households than blocks containing dispersed households (i.e., homes with acreage, rural land). Information typically available for census blocks includes population count, sex, age, race, Hispanic/Latino/Spanish origin, family structure, and home ownership. Block group is the next smallest spatial scale. Block groups are comprised of multiple blocks, and block boundaries are never split by block groups. This is the smallest spatial scale for long form (sampled) population data. All data collected by block are available at the block group level. Data can be aggregated to lower resolution scales including zip codes, census tracts, and counties.

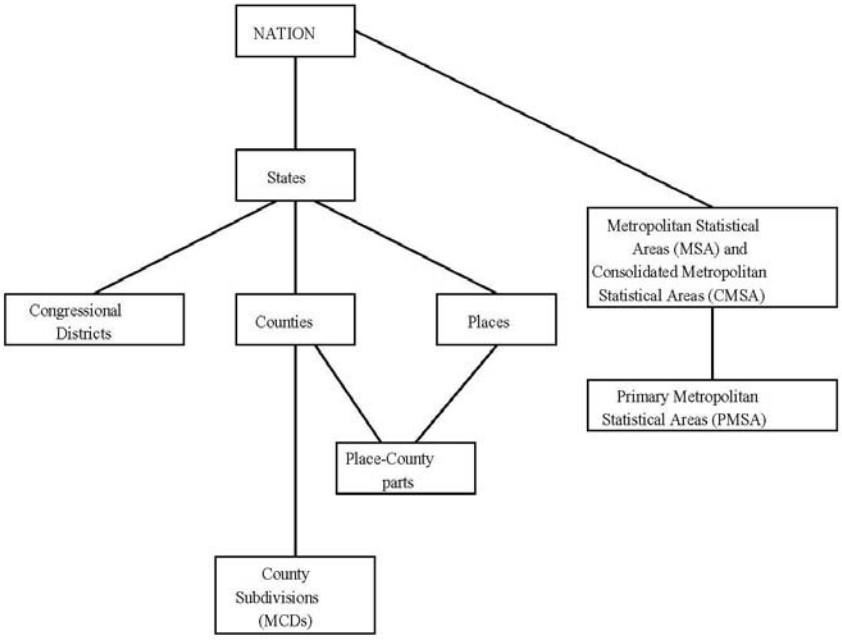
AIANHH:	American Indian area/Alaska Native area/Hawaiian homeland
ANRC:	Alaska Native Regional Corporation
BG:	Block Group
CD:	Congressional District
MA:	Metropolitan Area
SLD:	Sate Legislative District
TAZ:	Traffic Analysis Zone
UA:	Urban Area
UGA:	Urban Growth Area
VTD:	Voting District
ZCTA™:	ZIP Code® Tabulation Area

Source: [26]

Figure 2. Spatial Relationships among Census Bureau Geographical Entities

While the American Community Survey (ACS) is similarly comprehensive for urban areas, like the decennial census, it also fails to capture population data on a daytime basis. It too has a high level of spatial resolution which enhances the accuracy of population estimates, but data currently are not reported geographically at the block group or tract level for participating political units (see Figure 3). Instead, demographic data are

reported at the county sub-division level (i.e., MSD) or larger spatial scale. The ACS is intended to replace the Census long form in 2010. It uses a stratified sampling methodology to more accurately estimate population characteristics between decennial censuses at various temporal and geographic scales. Initially, a stratified sampling methodology is used to select 20% of households within census blocks without the possibility of reselection for 5 years. Household selection is stratified by the estimated variance of the occupied housing units within census blocks (or some other small geographic entity of interest) and census tracts by county. Estimates are based on information obtained from the most recent decennial census. After the initial selection of households to be sampled, a 3-month sample collection period within a one year period is randomly assigned to each household: survey forms are mailed in month 1; telephone interviews begin in month 2 if there is no response to the mailed survey, in-person interviews are attempted in month 3 if there is no response to telephone interviews. A small number of households are randomly selected for in-person interviews, stratified by the participation of mailed interviews. Beginning in 2006, the ACS included a stratified sample of group quarters which makes possible characterization of populations living in nursing homes, college dormitories, correctional facilities, shelters, and other group settings. Group quarter selection is stratified by size at the state rather than county level and group quarters that participate in the survey are eligible for re-selection every year.



Source: [27]

Figure 3. ACS Spatial Scale Relationships

Other Census Bureau products such as the Longitudinal Employer-Household Dyamics and the Census Transportation Package that do capture daytime data are far less comprehensive in terms of geographic coverage. Moreover, in their current form, their

spatial resolution tends to be lower than the decennial census and the ACS. In the future, coverage may be at a higher level of spatial resolution than the individual census block or tract making it possible to capture population data for specific buildings but confidentiality considerations may limit access to such high resolution data. However, because a deliberate release of radioactive material is likely to have a spatial scale that encompasses an area exceeding and/or cutting across census blocks or tracts such precision may be unnecessary for estimating the size of populations at risk to exposure to low-dose radiation from an RDD event [12].

InfoUSA illustrates the kind of open source population data available for purchase from commercial vendors as proprietary databases. InfoUSA, for example, compiles private and public databases from telephone directories, the US Census Bureau, US Postal Service, the Securities and Exchange Commission, and sources such as utility hook-ups and business registries to provide consumer and business contact information for marketing purposes [28]. Those marketing databases may be adaptable for determining current population counts to support estimating the size and spatial distribution of populations which may be exposed. Key demographic information relevant to incident management and medical response strategies includes location (zip code, radius, city, metro area, area code, and state), household income, gender, age, housing type, and the presence of children and/or seniors. The highest spatial resolution of consumer information is the zip code scale. Although data are temporally accurate for a specific month, because they are proprietary databases, the cost of acquisition may be prohibitive in some cases especially to maintain up-to-date records when an area is undergoing rapid changes in population.

Gravity Models for Spatial Interpolation of Population Distributions

Once the initial data source is selected, those data can be manipulated to calculate shifts in daytime versus night-time population counts and densities linked to specific geographic areas of interest. This can be done mathematically by using a gravity model of migration [29-31]. As the name implies, this model is analogous to Newton's law of gravitation in the sense that it predicts the degree of interaction between two locations as a function of spatial separation. Variants of the model have been used by social scientists for more than a century to characterize the movement of people, information, and commodities between two places [32-37]. Model calibration is accomplished empirically by adjusting parameter values (constant and exponents) to insure that the estimated results, when compared to actual observations, are similar to observed flows.

Gravity models empirically define the relationships between an origin (i.e., location of worker residences) and destinations (i.e., centers of employment). In essence, when applied to human interactions, the gravity model postulates that flows of people between geographical areas are directly proportional to the relative attractiveness of each area and are inversely proportional to some function of the spatial separation between them. Mathematically, in order to reflect this assumption, the gravity model is stated as follows in its most simple formulation:

$$M_{ij} = \frac{P_i P_j}{d_{ij}} \qquad \text{(Eq. 1)}$$

Where:

M_{ij} = flow between the two areas i and j respectively

P_i and P_j = values of parameter for areas i and j respectively

d_{ij} = distance between areas i and j respectively

Thus, spatial interactions between locations *i* and *j* are proportional to their respective importance divided by their distance. The values for P are assumed to be influenced by the relative "attractiveness" and "accessibility" of each area [38]. Attractiveness is a measure of the destination location's appeal relative to other locations. Accessibility is an index weighted by a combination of each area's attractiveness and a measure of distance from the origin (centroid) between each area. While static in the model, the values of the parameters are likely to change over extended periods of time. Traditionally, it is assumed that the further apart the two areas are the less movement between them is assumed to occur due to the phenomenon of distance decay. The effect of distance, however, is not really uniform (i.e., monotonic inverse relationship) but rather one in which distance is raised to some power other than unity [39]. For example, a constant exponent cannot yield reasonable results unless the range between the longest and the shortest distances between all pairs of areas is small. As a result, one of the underlying problems in determining values for the exponent is the variation in the measure used to express distance. This makes it necessary to apply a distance-decay function and a friction coefficient to scale the response to be consistent with measures of long or short distances [29, 38-41]. And, constraining both the origins and destinations (i.e., double constraint) ensures that the total flows estimated by the model equate the total flows observed for each area.

The general formulation of the model summarized above normally has to be extended by summing the count for all pairs of origins and destinations within the geographical area of interest to derive separate estimates for daytime and/or night-time that can be used to allocate populations. Doing this provides a technique for distributing population counts or densities based on daytime and night-time shifts between residences and places of work. The result is typically a matrix that provides population data for each origin-destination pair that can be displayed in a GIS environment. When matched to spatially distributed estimates of total dose equivalents, it becomes possible to calculate a first approximation of the potential severity of an intentional release of radioactive material during a RDD event.

DISCUSSSION AND IMPLICATIONS

The gravity model offers a straight-forward, empirical tool for estimating population flows, especially when geographical areas are relatively well-defined in terms of accessibility and spatial separation. This is particularly important for several reasons. First, the spatial scale for the area impacted by a RDD terrorism event is unlikely to match fully the spatial scale of available population data. That is, the plume spread typically will not uniformly overlay the impacted area. Second, the number of people within the impacted area varies as a function whether an attack occurs during the day or night. For example, the population of a central business district or industrial area typically is larger during the day while predominately residential areas have larger night-

time populations. As a result, interpolation techniques that link population data to geographical units and allocate those data based on timeframe at a spatial scale that is relevant to enhancing preparedness and response.

The gravity model's main advantage is that it efficiently allocates readily available, open source population data to geographical units appropriate for planning and implementing incident management and medical monitoring strategies. The importance of being able to link population estimates to geographic areas during the course of an RDD incident can be understood intuitively:

- The spatial distribution of actual total dose equivalents of ionizing radiation is likely to vary due to changes in meteorological parameters as an event evolves over time
- The size of the geographical area affected also is likely to vary as a function of the actual release scenario
- The ability to identify the location and size of the populations that may be exposed to doses of ionizing radiation is critical to carrying out appropriate treatment and post-event medical monitoring
- Once a spatial interaction model has been validated for a city or a region, it can then be used for simulation and prediction purposes to assess the possible human health consequences of different release scenarios

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