# Spatial Interaction Modeling to Identify Potentially Exposed Populations during RDD or IND Terrorism Incidents – 9443

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## ABSTRACT

Homeland Security Presidential Directive #5 (HSPD-5) *Management of Domestic Incidents and Department of Homeland Security (DHS) Planning Guidance for Protection and Recovery Following Radiological Dispersal Device (RDD) and Improvised Nuclear Device (IND) Incidents* underscore the need to delineate radiological emergency guidance applicable to remedial action and recovery following an RDD or IND incident. Rapid delineation of the population potentially exposed to ionizing radiation from fallout during terrorist incidents involving RDDs or low-yield nuclear devices (≤ 20KT) is necessary for effective medical response and incident management as part of the recovery process. This paper illustrates the application of spatial interaction models to allocate population data for a representative U.S. urban area (≈1.3M people; 1,612.27 km$^2$ area) at a geographical scale relevant for accurately estimating risk given dose concentrations. Estimated total dose equivalents (TEDE) are calculated for isopleths moving away from the detonation point for typical release scenarios. Population is estimated within the TEDE zones using Euclidean distances between zip code polygon centroids generated in ArcGIS version 9.1 with distance decay determined by regression analysis to apportion origin-destination pairs to a population count and density matrix on a spatial basis for daytime and night-time release scenarios.

## INTRODUCTION

Terrorist use of a Radiological Dispersal Device (RDD), commonly called a dirty bomb, or an Improvised Nuclear Device (IND) can distribute ionizing radiation from at most a few kilometers to widespread dispersion across a major metropolitan area. As a result, predicting the likely location and size of populations potentially exposed to ionizing radiation from fallout during terrorist incidents (pool of potential human targets) involving RDDs or low-yield nuclear devices (≤ 20KT) is necessary for designing and implementing effective triage and medical management of casualties based on rapid, non-invasive estimation of radiation exposure [1-5]. 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 – including post-event mental health interventions – especially when it is not possible to observe directly adverse health effects in the absence of acute radiation sickness (ARS), commonly referred to as radiation sickness [6-8].

With exposure to radiation, clinical manifestations of physiological effects are contingent on the absorbed dose of radiation. For the victims of an RDD as well as those who are not casualties due to the prompt radiation from an IND, the radiation dose will be below the threshold for ARS of whole-body or significant partial-body irradiation > 1 Gy delivered at a relatively high dose rate but still produce exposure to ionizing radiation. Additionally, various tissues differ as to their response to ionizing radiation underscoring the importance of establishing measurable endpoints linked to dose [9, 10]. Moreover, because clinical manifestations of psychological effects also may occur subsequent to an incident, this also can aid in identifying target areas for developing effective post-event mental health interventions [11]. Unfortunately, the spatial scale for the area impacted is unlikely to match fully the spatial scale of available population data. That is, the plume spread and corresponding initial dose of radioactive material do not uniformly overlay the impacted area. Second, the number of people within the impacted area varies as a function when an attack occurs (e.g., 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.

Because severity expressed as mortality and morbidity partially is contingent on the pool of potential targets, accurate population data coupled with dose estimates 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 [12]. 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 to contain and mitigate consequences, and reduce potential cross contamination. Spatial interaction models, also called gravity models, estimate the movement of resources (in this case people) from one location to another based on the attractiveness of the destination and the distance between the locations [13-17]. The model re-allocates the population from locations where they reside to locations where they are likely to work during the day. This makes it possible to generate daytime and nighttime estimates of the size and spatial distribution of a potentially exposed population in the event of a terrorist attack.

## METHODS

Spatial interaction models provide a tool to allocate population data at a geographical scale relevant for accurately estimating risk given dose concentrations. 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. Geographical information systems (GIS) coupled with computational algorithms provide a convenient approach for using open source population data to estimate the size and location of populations potentially exposed to ionizing radiation released by RDDs or INDs during terrorism incidents.

### Release Scenarios

We consider a set of simulated scenarios in which terrorists use a RDD or an IND in an urban area to maximize impact in terms of physiological and psychological effects in order to illustrate the application of spatial interaction modeling as a screening tool for estimating the size and spatial distribution of potentially exposed populations. The dirty bomb and improvised nuclear device scenarios examined in this analysis are consistent with plausible threats. The RDD incident was assumed to have released 291.34 g of Am-241 with an activity level equaling $3.7 \times 10^{13}$ Bq (1 KCi) using 45 kg TNT (trinitrotoluene) equivalents equal to of high explosives (i.e., military-grade such as Semtex). The Am-241 source term is an alpha and gamma radiation emitter with a 432.2 year half-life and a specific activity $0.127 \times 10^{12}$ Bq/g. The nuclear terrorism scenario involves the detonation of a crude nuclear device using either Pu or HEU at ground level with a 10KT yield blast equivalent (one ton corresponds to the energy of $4.2 \times 10^{9}$ J released by the explosion of $10^{3}$ kg of TNT; a *fizzle* from improper design or physical stress may produce a yield as low as $10^{-2}$ KT). We use these basic scenarios because each is readily scalable to increasing or decreasing source terms.

Each scenario is further characterized by assumptions about the: (1) type of device used; (2) meteorological conditions – wind speed, wind direction, atmospheric stability, precipitation; (3) time of day – daytime versus night time. Wind speed and direction values were derived from the Climatic Wind Data for the United States [18]. This analysis considers two different wind speed/wind direction parameters based on historical monitoring data. In general, the more unstable the atmosphere, the greater the vertical dispersion of radioactive aerosols which reduces concentrations deposited at a given location. Pasquill atmospheric stability class based on wind speed provides a means for incorporating this parameter into the model [19]. For the RDD scenario, we consider four atmospheric stability classes: very unstable (A); neutral (D); moderately stable (F); and night (G) to provide insight into the effect of stability class on estimated dose. The nuclear explosion immediately creates an unstable atmosphere. For both set of scenarios, we consider the effects of detonation while raining and detonation while not raining using a simple source depletion method is used to account for washout during precipitation with rainfall occurring simultaneously with release [20]. This gives us a total of 16 RDD scenarios and 2 IND scenarios with which to demonstrate the application of spatial interaction modeling to identify potentially exposed populations during RDD or IND terrorism incidents.

**Study Area**

For this analysis, we selected a southwestern U.S. metropolitan area as the study site (population ≈1.3M people; encompasses 1,612.27 km$^2$). We assumed that a RDD or an IND is detonated approximately 1.5 km north of the junction of three major east-west, north-south freeways near the downtown central business district (Figure 1).


**Figure 1. Study area and detonation location**

**Total Dose Equivalent Estimation**

Estimated total dose equivalents (TEDE) are calculated for isopleths moving away from the detonation point for typical release scenarios. The Hotspot Model Version 2.06, developed by Lawrence Livermore National Laboratory, was used to generate TEDE values for the dirty bomb and improvised nuclear device scenarios [21]. The Hotspot code incorporates Federal Guidance Reports 11, 12, and 13 Dose Conversion Factors to provide first-order approximation of radiation effects associated with atmospheric releases of fissile and non-fissile material. Hotspot uses a simple, two-dimensional Gaussian plume model to represent dispersion and runs in a Windows operating system environment. The model then simulates the dispersion of radioactive material as it moves downwind away from the initial detonation point. As the plume moves through the urban terrain subsequent to the initial release, it increases spatially in the horizontal and vertical directions. The dispersion of the Am-241 over the computational domain is determined by wind speed, direction, stability class, precipitation, and estimated source term area dimensions. Yield, wind speed, and wind direction are the primary factors controlling dispersion for the nuclear explosion scenario. Hotspot is designed for short-term releases of radioactive material (duration < 24 hours) and provides screening estimates of the initial dose on a spatial basis in terms of the immediate downwind radiological impact. Therefore, although a three-dimensional model that incorporates fully Navier-Stokes equations typically will provide better estimates for complex urban environments, the approximations provided by this solution are suitable for application to this analysis.

**Spatial Interaction Model Estimation**

The major open sources of data on the U.S. civilian population have limitations, especially in terms of trading off high spatial resolution for high temporal accuracy. Moreover, the quality of estimates of populations 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 [22]. As a result, computational algorithms must 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 [23-26]. Spatial interaction models, frequently referred to a gravity models, offer a straight-forward solution to this problem.

In essence, the technique quantifies the relationships between an origin and a destination while accounting for distance between the locations using a distance decay or power distance decay function [15, 17, 27]. In essence, 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 to characterize the movement of people between two places. 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. 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

For this analysis, we opt to estimate spatial interaction models using the ArcPlot module of the ArcInfo Workstation component of ArcGIS version 9.1 using 2000 decennial census and 2005 zip code business patterns data [14]. Zip codes were obtained for the year 2000 from the Census Bureau 2002 Tiger line files [28]. This spatial scale was selected because it was the highest resolution scale for which publicly available data were available that provided the numbers of workers residing and employed at specific locations. This information was arrayed in a geo-database for summarization using built-in database functions and displayed in the ArcMap component of ArcGIS. The temporal scale varied by dataset. The numbers of workers employed at a zip code were available from Zip Code Business Patterns (ZBP), an annual survey of employers by the US Census Bureau, for the years 2000 and 2005 [29, 30]. Once the initial data source was selected, those data were manipulated to calculate shifts in daytime versus night-time population counts and densities linked to specific geographic areas of interest using a power distance-decay function and a friction coefficient to scale the response to be consistent with measures of long or short distances [13, 31-33]. 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 was 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 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 population counts allocated spatially on a daytime and night time basis.

The numbers of workers residing and employed in a zip code was determined for selected NAICS categories, and spatial interaction models were estimated for each of these categories. To get an unbiased estimate of distance decay, application of the $\log_{10}$ transformation to the dependent variable (number of employees commuting) and the predictor (distance travel to work) was necessary to linearize the relationship to estimate the distance decay exponent. Travel time to work was used to determine the distance traveled to work and estimate a distance decay coefficient. These data were provided by the 2000 decennial census for the zip code spatial scale, but were not industry-specific. The commuting time to work (minutes) by zip code was extracted for the state and grouped into 12 categories with midpoints from 2.5 to 90 minutes. Each mid-point category value was multiplied by 64.4 km/hour (40 mph) to estimate travel distance to work. This speed represents a median value between speeds posted for local roads, city/county main roads, and interstate highways in the metropolitan area. The distance decay exponent value (-0.64) was estimated using linear regression.

Once the distance decay exponent was determined, the spatial interaction model could be estimated for each NAICS category. The model was estimated using the 2000 decennial census and ZBP data to determine the zip code within which workers resided (employee origins) for all potential employment centers (destinations) [28, 29]. We constrained the spatial interaction model, using an attraction constraint because the most up-to-date information available was from ZPB 2005, to estimate the zip code population count in 2005. The attraction-based spatial interaction model constrains the numbers of workers employed at a zip code to match the number observed as being employed at that zip code. The numbers of employees residing in a zip code were allowed to vary to meet the constraint.

**Regression Analysis**

The spatial interaction model output was used as input for the regression analysis to generate forecasts of population in out-years. Regression techniques in SAS version 9.1 were used to determine the relationships between the total population of a zip code and the number of workers in each NAICS category residing in a zip code [34]. The year 2000 total population of a zip code was the dependent variable, and the independent variables were the number of workers for each NAICS class estimated by the spatial interaction models to be residing in the zip code in 2000. We used the regression analysis to extrapolate population counts from 2000 to 2005 based on the coefficients estimated using only the 2000 census and ZPB data to estimate 2005 total population in each zip code. A log transformation of population counts ensured that negative population counts did not occur. Scaling by the area of the zip code corrects for heteroskedasticity. Model errors were evaluated to determine appropriate functional forms. The regression model was also checked for multicollinearity. Model fit was evaluated based on adjusted $R^2$, root mean square error (RMSE), and jackknife residual error.

**RESULTS**

TEDE values expressed in Sieverts (Sv) were calculated for each of the release scenarios. Figure 2(a) shows that the RDD scenarios typically result in the spread of radioactive material, in this case Am-241, over a range of several $km^2$. And, because the level of radioactivity is limited, the TEDE tends to be relatively low with the highest predicted dose zone equaling $5 \times 10^{-4}$ Sv. On the other hand, as Figure 2(b) indicates, the IND – in this case a device with a 10KT yield – distributes a much larger volume of radioactive material over a much larger spatial domain ranging out to nearly 100 $km^2$. The detonation of an improvised nuclear device scenario has predicted TEDE values orders of magnitude higher than the RDD scenarios.

In parallel to calculating the TEDE values for each of the RDD and IND scenarios, we predicted the population counts distributed across the study area. Figure 3 illustrates the night-time value. While we only present one example in this paper, we generated a similar distribution for the day-time population at the same spatial scale (zip code). Not surprisingly, the population count varies temporally with because day-time reflects employment patterns and night-time reflects residence. This allows us to match population counts to the TEDE values to derive a spatially-distributed estimate of the potentially exposed population for each scenario on a day-time or night-time basis.

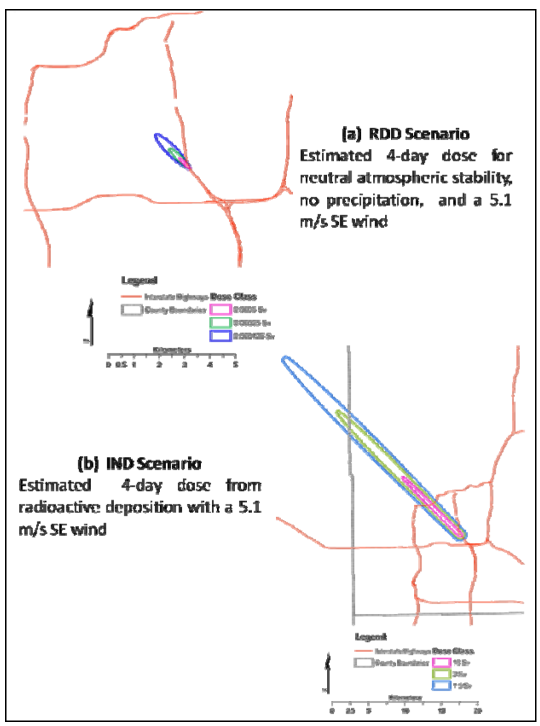


**Figure 2. Total dose equivalent isopleths (Sv) for representative RDD and IND scenarios**

Figure 4 illustrates how the output from the spatial interaction model is linked to the predictions of total estimated dose equivalents produced by the various RDD and IND scenarios. In this case, we opt to display the results from a night-time detonation of an improvised nuclear device. The overlay of the dose prediction isopleths on the population distribution indicates graphically a first approximation for the number of people who potentially might be exposed to ionizing radiation since fatalities from the blast and thermal effects are not excluded. A similar graphical display can be produced for each of the other scenarios we evaluated. In addition, a table can be generated for the set of scenarios providing more detailed information about the scenario specifics such as type of attack and meteorological conditions, day or night event, the predicted TEDE values associated with the scenario, and the size as well as location of the potentially exposed population.

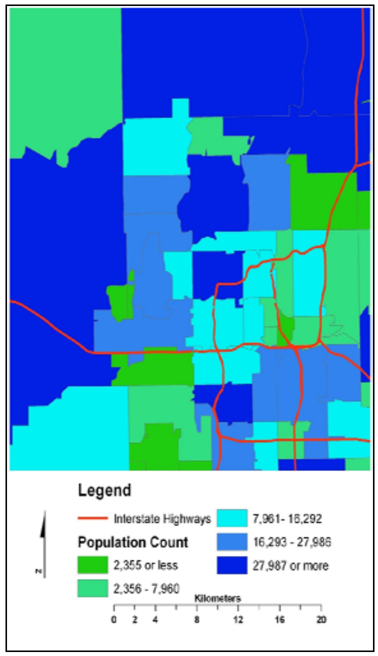


**Figure 3. Night-time population counts at zip code level**

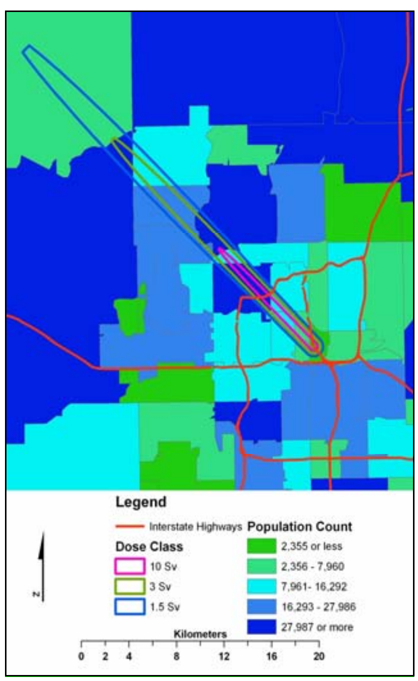

**Figure 4. Spatial distribution of potentially exposed night-time population counts by TEDE isopleths (Sv) for representative IND scenario**

Table 1 presents an estimate of the number of people likely exposed to Am-241 as a result of the dirty bomb detonation scenarios. We make the protective assumption that the entire population within a zip code reached by the plume may potentially be exposed to at least 0.125 mSv TEDE. This is also necessary because determining the distribution of the population within a zip code is impossible using the available data. It is evident that meteorological conditions (stability, wind speed and direction, and precipitation) may greatly affect exposure. The greatest exposure is likely to occur in highly stable conditions because of the lack of vertical mixing in such conditions. Precipitation may reduce the size of the plume by washing out some of the suspended material. Wind speed influences how rapidly the plume spreads while direction impacts which locations lay in the path of the plume. Table 1 also shows that the time of day of the detonation may greatly influence the number of people exposed. We estimated approximately 500% more people potentially would be exposed in the day than at night because the detonation occurs in an area that increases population during the day because of employment. The increase does not include estimates of consumers seeking goods and services within this area, only those employed by industries within the zip code.

**Table 1. Estimated number of people potentially exposed to the plume from the detonation of a dirty bomb**

| Scenario Information | | | | Dose Class | | |
|---|---|---|---|---|---|---|
| **Day/Night** | **Wind** | **Rain** | **Stability** | **0.125 to <0.25 mSv** | **0.25 to <0.5 mSv** | **≥0.5 mSv** |
| DAY | North (6.3 m/s) | No Rain | Very Unstable | 12,116 | 12,116 | 12,116 |
| | | | Neutral | 38,734 | 12,116 | 12,116 |
| | | | Moderately Stable | 60,002 | 12,116 | 12,116 |
| | | Rain | Very Unstable | 12,116 | 12,116 | 12,116 |
| | | | Neutral | 38,734 | 12,116 | 12,116 |
| | | | Moderately Stable | 38,734 | 12,116 | 12,116 |
| | Southeast (5.1 m/s) | No Rain | Very Unstable | 35,372 | 30,690 | 12,116 |
| | | | Neutral | 35,372 | 35,372 | 35,372 |
| | | | Moderately Stable | 50,223 | 35,372 | 35,372 |
| | | Rain | Very Unstable | 35,372 | 30,690 | 12,116 |
| | | | Neutral | 35,372 | 35,372 | 30,690 |
| | | | Moderately Stable | 35,372 | 35,372 | 35,372 |
| NIGHT | North (6.3 m/s) | No Rain | Night | 1,890 | 1,890 | 1,890 |
| | | | Night | 10,019 | 5,630 | 1,890 |
| | Southeast (5.1 m/s) | Rain | Night | 1,890 | 1,890 | 1,890 |
| | | | Night | 10,019 | 1,890 | 1,890 |

Table 2 provides a summary of the number of people potentially exposed to the plume associated with the detonation of 10kT improvised nuclear device detonated at ground level. Obviously, the magnitude of the event potentially directly affects an order of magnitude more people than an RDD event. Not explicitly considered in the estimates in Table 2 is the number of people potentially harmed by blast, thermal and acute radiation effects that will result in death for those closest to the detonation location. We opt not to do this so the RDD and IND scenarios can be compared in terms of TEDE from fallout. Once again, we assume the entire population within a zip code is potentially exposed if the plume is projected to reach a zip code.

**Table 2. Estimated number of people exposed to the plume from the detonation of an improvised nuclear device**

| **Scenario Information** | | **Dose Class** | | |
|---|---|---|---|---|
| **Wind** | **Day/Night** | **1.5 to <3 Sv** | **3 to <10 Sv** | **≥10 Sv** |
| North | Day | 232,757 | 219,422 | 116,503 |
| (6.3 m/s) | Night | 247,203 | 229,558 | 123,224 |
| Southeast | Day | 282,766 | 282,766 | 165,128 |
| (5.1 m/s) | Night | 247,203 | 229,558 | 123,224 |

## CONCLUSIONS

The results of our simulations clearly demonstrate the catastrophic implications of terrorists using a low yield nuclear weapon. In addition to the immediate casualties due to prompt ionizing radiation as well as the blast and thermal effects from a nuclear detonation, detonation of an IND in an urban area would immediately cause widespread dispersion and deposition of highly radioactive material across literally thousands of $km^2$, with corresponding exposure risk to downwind populations. Moreover, although our analysis does not address explicitly the loss of life due to the blast, thermal, and prompt ionizing radiological exposure effects associated with nuclear terrorism, the approach also can be applied to derive estimates of the population within the impact zone for those effects. And, with respect specifically to ionizing radiation, the simulations presented in this paper underscore the relatively low doses likely to happen using a high explosive to detonate a RDD compared to the high doses from an IND.

The importance of being able to link population estimates to geographic areas during the course of an RDD or an IND incident can be understood intuitively. The spatial distribution of actual total dose equivalents of ionizing radiation is varies due to changes in meteorological parameters as an event evolves over time. The size of the geographical area affected also varies as a function of the actual attack scenario. Delineating the location and size of the populations that may be exposed to doses of ionizing radiation is critical to implementing appropriate treatment and post-event medical monitoring. Hence, the approach to spatial interaction modeling outlined in this paper offers a useful tool for quantifying the size and geographical distribution of populations potentially exposed to ionizing radiation during radiological or nuclear terrorism incidents.

The technique is very flexible and efficiently allocates readily available, open source population data to geographical units based on timeframe at a spatial scale that is relevant are essential for planning and implementing incident management and medical monitoring strategies. Application of the technique to a series of representative scenarios demonstrates the approach generates a first approximation of population flows, especially when geographical areas are relatively well-defined in terms of accessibility and spatial separation. And, once a spatial interaction model has been validated for a city or a region, it can be used for simulations to predict the possible human health consequences of different release scenarios. As a result, provided initial input data are available with which to estimate population parameters, this modeling approach can be applied to indicate which scenarios are particularly problematic with respect to the atmospheric release of radioactive material in urban areas.

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