Environmental Justice and Hazmat Transport: A Spatial Analysis in Southern California

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FORTHCOMING IN TRANSPORTATION RESEARCH PART D

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This manuscript explores the question: is the risk of a toxic release during transport greater in poor and minority neighborhoods? The study uses a combination of mapping and statistical methods. A geographical information system is used to locate transport spills and handlers on a digital map. Cluster analysis methods examine the density of facilities and transport spill events as well as tests for the spatial covariance between facilities and spills. Cluster analysis demonstrates strong clustering of transport spills, as well as clustering between factory sites and transport spills. A spatial model demonstrates raised rates of transport spills surrounding clusters of toxic firms. In fact, most spills in Los Angeles occurred within 2 km of an intermodal facility. The last step of the analysis compares risk and facility clustering between neighborhoods and socio-economic groups, finding that hazmat spills during transport disproportionately occur in Latino neighborhoods in Los Angeles. The results of this clarify the spatial distribution of risk and nuisance from industrial production in urban landscapes.

Keywords: hazardous materials transportation, environmental justice, freight, land use

Introduction

Environmental justice activists claim that low-income and minority communities become "environmental sacrifice zones"—places where toxic or hazardous industries agglomerate in the built environment (Bullard 1995). Hazardous materials releases can occur both on-site and off-site during transport, which suggests that a combination of industrial land and freight infrastructure in tandem create both unsightly and, according to some, dangerous land areas in cities. This article examines how industrial land and freight traffic influence the spatial and socio-demographic distribution of hazmat transport risks by means of a case study of the Los Angeles metropolitan region.

The risks associated with hazardous materials transport has been a continuing concern for community residents informing case study research in environmental justice:

> Buttonwillow is also the host to one of California's three toxic waste dumps, the Lokern facility, run by a Canadian toxic waste dumping company. Highway 58, until recently the main route for trucks filled with toxic waste bound for the dump, runs through the middle of town and past the local elementary school...At times, more than 200 trucks a day would whiz by the school, carrying their toxic load. "The trucks carrying toxic waste come through town, and they park at the local restaurant, and we can smell the stuff coming out," says a Buttonwillow resident, Saul Moreno (Cole and Foster 2001:18).

These concerns are echoed by environmental justice activists concerned about risks in other regions, such as Louisiana's Cancer Alley (Roberts and Weiss 2001). How much nuisance and risk might freight traffic add to existing industrial land uses? Table 1 summarizes the prevalence of hazmat shipping in the US; ever year, companies ship over 263 million ton-miles of hazmat; over 60 percent of that is on tucks. Over 155,550 incidents occurred which caused over 3,950 injuries, 200 deaths, and $499,746,084 in damages from 1993 to 2002.[1] California had the highest spill number of any state. Spill

[1] Data compiled by the author from the Hazardous Materials Information System: downloadable at the Bureau of Transportation Statistics website: http://www.transtats.bts.gov/ .

frequency is increasing overall and in California, because freight traffic is on the rise in both the US and transnationally (Saricks and Tompkins 1999).

Table 1. Total estimated shipments by mode in US, 1997[†]

	Value		Tons		Ton-miles	
	($ million)	**Percent**	**(thousands)**	**Percent**	**(millions)**	**Percent**
TOTAL all modes	**466.4**	**100.0**	**1,565.2**	**100.0**	**263.8**	**100.0**
Single modes, total	**452.7**	**97.1**	**1,541.7**	**98.5**	**258.9**	**98.1**
Truck	298.2	63.9	869.8	55.6	74.9	28.4
For-hire	134.3	28.8	336.4	21.5	45.2	17.1
Private	160.7	34.5	522.7	33.4	28.8	10.9
Rail	33.3	7.1	96.6	6.2	74.7	28.3
Water	27.0	5.8	143.2	9.1	68.2	25.9
Air	8.6	1.8	0.1	–	0.1	–
Pipeline	85.7	18.4	432.1	27.6	S	S
Multiple modes, total	**5.7**	**1.2**	**6.0**	**0.4**	**3.1**	**1.2**
Parcel, U.S. Postal Service or Courier	2.9	0.6	0.1	–	0.1	–
Other	2.9	0.6	5.9	0.4	3.0	1.1
Unknown and other total	**7.9**	**1.7**	**17.5**	**1.1**	**1.8**	**0.7**

[†]U.S. Department of Transportation, Bureau of Transportation Statistics, U.S. Department of Commerce, Census Bureau, *1997 Economic Census*, *Transportation, 1997 Commodity Flow Survey, Hazardous Materials* (Washington, DC: December 1999), table 1.

While the number of injuries and fatalities associated with spills are low compared to other causes of death or disease, community residents still dread exposure to toxics from trucks in their neighborhoods (Roberts and Weiss 2001). Few studies have systematically examined the distribution of hazardous materials exposure from transport routing or spills, and none have done so using explicitly spatial methods based on proximity to industrial land.

Conceptual framework

In this analysis, I will test the hypothesis that low-income and minority residential proximity to factories increases exposure to risk from hazmat spills using data drawn from four counties in Southern California. Throughout this manuscript, I use a simple definition of risk: risk is the possibility of a hazmat incident. No measures of exposure or potential exposures are used. Rather, the analysis considers event frequencies.

At least three things could explain why communities of color may be at higher risk from transport spills:

1. Low-income individuals and people of color reside near hazmat freight routes in disproproportionate numbers;

2. Industries generate hamzat freight, and if impoverished communities of color are located disproportionately near industrial land uses, they will therefore be at greater risk from hazmat incidents; or

3. both 1 and 2.

There is a subtle distinction between the first two possible sources of heightened risk. In the first, risk is associated with the route; residents living, for example, along the line-haul portion of a hazmat shipment may be very far (or not) from the shipment's origin or destination. In the second case, the risk for a hazmat spill is elevated near the origin or the destination of the trip. Because people of color and low-income groups have been found to live closer to industrial land (origins and destinations) than other groups, they would be subject to greater risk. These two factors are not mutually exclusive. Low-income and minority persons may be both found in greater numbers along routes and near origins and destinations. Thus, disparities in risk can arise from different sources, depending on how hazmat spills are distributed through transportation networks.

Previous approaches to risks from hazmat transport

The existing research has sought most often to derive risk-minimizing routes (the first source of possible risk disparity). In some cases, these routes are optimized using algorithms to consider socio-demographic information and environmental justice (Verter and Kara 2001). Another major strand of hazmat transport research examines the empirical data record to uncover the major causes and consequences of previous hazmat incidents. An examination of both demonstrates that current methods of modeling hazmat miss the environmental justice claim about the special risks associated with living near both industry and highways rather than just along the highway alone.

Descriptive studies examine the spill and accident record over time to find the common causes and consequences of hazmat releases during transport. In one such descriptive analysis, Horton et al. (2003) look at the consequences of acute exposures from hazmat incidents from 1993 to 2000. They use the Agency for Toxic Substances and Disease Registry's Hazardous Substances Emergency Substances Events Surveillance System. They found that human error and equipment failure—not collisions—were the most prevalent spill causes.

(Vilchez, 1995 #220) contradict these findings their examination of international spills. They used the Major Hazard Incident Data Service from the Major Hazard Assessment Unit in the United Kingdom. These data describe incidents in the US, Canada, the UK, France, and India from 1900 to 1992. They found that of the 5,325 cases they studied, 39 percent occurred during transport. Of those, 35 percent were due to rail accidents, and 25 percent were due to road crashes. They find that loading and unloading materials is an especially dangerous activity and deserves more attention due to its prevalence as a factor in both on- and off-site chemical release. In another international study, (Christou 1999) analyzed a world-wide database of 617 accidents at marshalling yards and ports, or what the author calls "transportation interfaces." He demonstrates that some of the incidents at transfer points—where shipments are loaded and unloaded—have had high consequences, in terms of evacuations, injuries, and fatalities.

A study of hazmat incidents in Pennsylvania compared three databases: 1) the state of Pennsylvania traffic accident database, 2) the federal Bureau of Motor Carrier Safety (BMCS) truck accident database, and 3) the Hazardous Materials Information Reporting System data (Hobeika et al. 1993). The descriptive analysis looked at the data for 1971 to 1983. The state DOT data, reported by police and highway patrol, record more incidents and more fatalities than either the HMIRS or BMCS data. Based on this, the authors conclude that the federal data under-report spills. They also conclude that although incidents due to human error are more numerous, more incidents and fatalities result from crashes involving hazmat incidents.

But the authors do not differentiate—as the state DOT data did not differentiate—between crash-related injuries and those caused from exposure to the release. The federal databases record only injuries and fatalities associated with release. If in fact an injury or fatality resulted from a collision rather than chemical release, then it really does not matter than the incident involved hazardous freight; getting hit by a truck is one thing, dying from chlorine inhalation is another. Battelle (2001) demonstrates that enroute accidents (i.e., those accidents that do not occur during load and unloading) account for about 89 percent of total damage. Only 40 percent of that amount is accounted for by hazardous materials releases; the rest is vehicle collision and property damage. In the first case—far rarer—where the injury or fatality resulted from chemical exposure, then the type of shipment involved in the crash is indeed germane.

In contrast to the descriptive studies, modeling studies have used GIS extensively. Verter and Kara (2001) perform a GIS-based risk assessment of gasoline, fuel oil, petroleum, and coal tar in Quebec and Ontario. They map the origin, destination, material type, monetary value, and number of trucks used in each shipment on a comprehensive highway network. They also apply their results to examine the risk equity based on the population near route links. Depending on the highway network, significant gains in risk reduction occur by conditioning the shortest-path on potential population exposure. The researchers found trade-offs in risk equity between possible routes; they also found that the route that minimizes population risk overall.

While Verter and Kara use buffers to represent the exposure zone, Leonelli et al. 1999 employ models to explore the spatial area of effect. Like Verter and Kara, however, they offer two approaches: one designed to measure individual risk, and another to examine the societal risks associated with hazardous materials transportation. They consider particular substance properties such as stability, meteorological and seasonal conditions, indoor and outdoor population, and non-uniform population densities. Unlike the theoretical approach offered in Leonelli et al. (1999), Brainard et al. (1996) use a regionwide, GIS-based approach to model routes for aqueous waste cargo in England. They evaluate risk according to the distribution of population and groundwater vulnerability. They use their methodology as a means for selecting a risk-minimizing route.

In an analysis of environmental justice, Margai (2001) uses an GIS database of Emergency Response Notification System (ERNS) data for Monroe and Suffolk County (New York) to analyze the hazmat incidents from 1997. This author uses buffers estimated according to potential chemical plumes. She finds using a stepwise analysis that in buffers from 0.5 to 2 miles from spill locations, the proportion of low-income and Hispanic residents is high.

The empirical research has demonstrated that, depending on the region studied, the routing criteria chosen and the relative weights given to those criteria portend different distributions of hazardous materials traffic within cities. Depending on the context, the route that minimizes overall population risk may not minimize exposure to low-income, minority, or other vulnerable residents. Some studies draw a buffer around links to address sensitive populations, while others incorporate a dispersion model and assumptions about possible human and ecological receptors of an incident. In each of these cases, there is the tendency to assume that incident probability is a function of the roadway environment rather than the distribution of industrial land uses within a metropolitan region.

Case Study Region and Data

The data used to conduct this analysis pertain to a four-county area in southern California that includes: Los Angeles, Orange, San Bernardino, and Riverside. The Los Angeles metropolitan region has a long history as a home to heavy industry: even now, the four-county area has over 12,000 facilities holding some form of hazardous materials permit. Table 2 compares the national spill distribution to the spill distribution in the case study region. The percentages of flammable liquids and corrosives in the Los Angeles case study area are slightly larger than for the US. Otherwise, the percentages track closely.

Transporters and first responders report basic information on every hazardous materials spill that happens, including its location, time of day that it occured, materials spilled, amount, carrier, and the number of people killed, injured and/or evacuated. These data, the Hazardous Materials Information System (HMIRS), are available for all US counties since 1993 from the U.S. Department of Transportation Office of Hazardous Materials Transportation (OHMT).

Table 2. US Hazardous materials shipments and spills by hazard class

	National Shipment Figures, 1997					National Spill counts 1992 to 2001		Study Region counts 1992 to 2001	
Class	**Ave Miles**	**Ton-miles**	**Percent**	**Tons**	**Percent**	**Spills (total)**	**Percent**	**Spills**	**Percent**
Total	113	263,809	100	1,565,196	100	151,601	100	3,823	100
1. Explosives	549	—	0	0	0	0	0	0	0
2. Gases	66	21,842	8	11,502	7	5,909	4	88	2
3. Flammable liquids	73	159,979	61	126,428	81	62,430	41	1,689	44
4. Flammable solids	838	9,618	4	11,804	1	1,442	1	25	1
5. Oxidizers	193	4,471	2	9,239	1	5,170	3	128	3
6. Toxics	402	2,824	1	6,366	0	11,143	7	254	7
7. Radioactive	445	0*	0	0*	0	155	0*	3	0*
8. Corrosives	201	41,161	16	91,564	6	59,360	39	1,516	40
9. Misc.	323	22,727	9	65,317	4	5,992	4	120	3

— Data are not reported by the Commodity Flow Survey due to high sampling variability

* Figure rounds to zero

Source: Data compiled by the author from the Hazardous Materials Information System Data, Retrieved October 2, 2004 from the Bureau of Transportation Statistics, on the World Wide Web; www.transtats.bts.gov

Spill data characteristics

Transport spill data include information on accidental releases during transport for all substances that are regulated by the Department of Transportation as well as many other chemicals. Carriers are required to report releases to the National Response Center (NRC) when a spill results in an injury or death; causes carrier or property damage over $50,000; requires evacuation of the general public; or closes a major transportation facility. First responder reports are collected initially over the phone and then transmitted to the Emergency Response Notification System. After the spill, carriers are required to submit written reports regarding the spill within 30 days. The Hazardous Materials Spills Information System data are the electronic compilation of these written reports.

HMIRS data pose some problems. Transporters of hazardous materials may carry a mixed cargo so that one accident event can result in the release of more than one substance, and the HMIRS records each of these substances as a separate spill even though they occurred simultaneously. On the one hand, this strategy makes sense; it is important to keep track of which materials were spilled and how. But treating mixed shipments spills as more than one accident event is misleading in a spatial analysis as it double counts (and at times, triple and quadruple-counts) mixed-shipment accidents over single-substance events. To address this problem, mixed spills are combined into a single event record, and a new binary variable marks events that contained more than one substance.

In addition, the HMIRS data are not listed by chemicals are listed only as flammable or as pesticides. Fortunately, there are not many records listed under such vague labels. Over 95 percent of the records are listed by a proper shipping name or chemical. Dummy variables are created for each hazard class in order to compile the data by hazard type (e.g., explosives, nuclear materials, flammables, etc), as shown in Table 2.

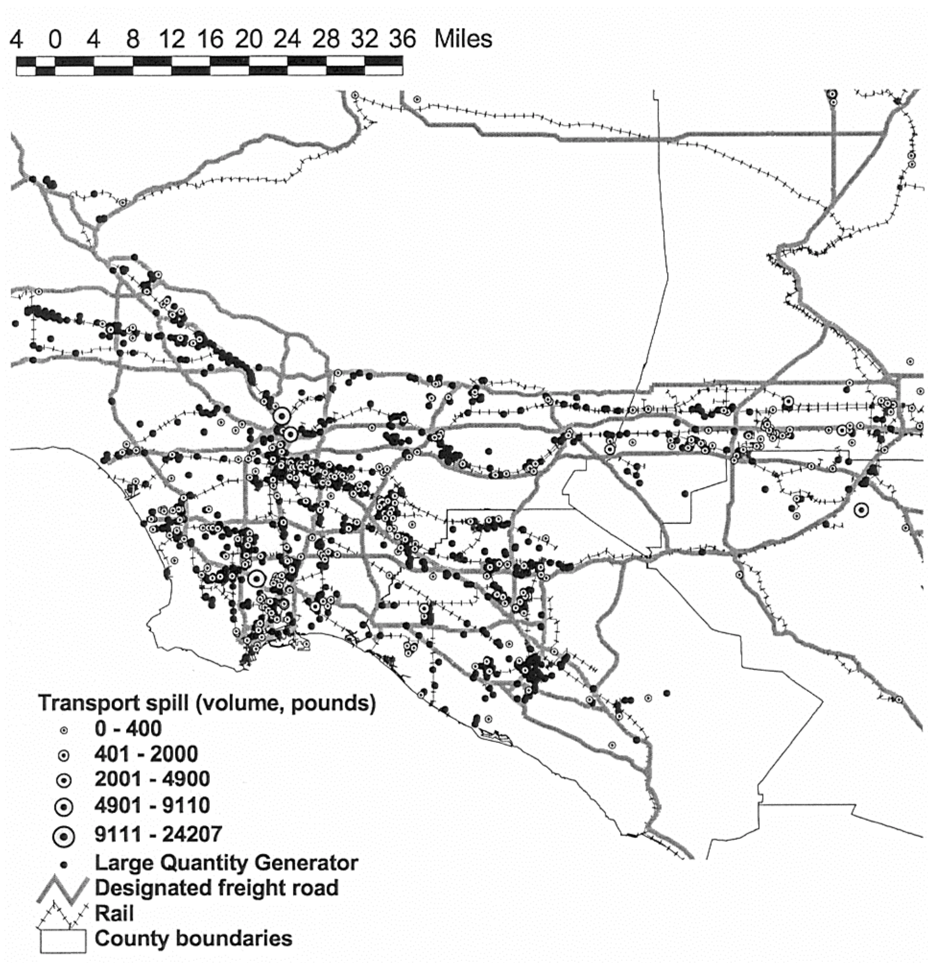
Although the HMIRS lists hazards by classification and spill volumes, there is no information on plume, although there is information on whether the release was liquid, vapor, fire, or explosion. Because there is no information on plume, spills are examined here as a marked point process, one that centers on the address reported for the spill. In some instances, the address information for the spill location is insufficient for address-matching/geocoding. These events were dropped from the analysis. From 1993 to 2002, there were 3,680 usable spills; I was able to geocode 550 spills (13 percent of 4,230 records).

Error! Reference source not found. is focused on the westernmost parts of Los Angeles and Orange counties. The figure shows the location of facilities permitted for hazmat (large quantity generators) juxtaposed with hazmat spills from both highway and rail modes.[2] It is difficult to make any summary statements about the two spatial patterns. Spatial correlation between LQGs and hazmat spills appears regularly in some clusters

[2] A Large Quantity Generator is a firm that regulated under the Resource Conservation and Recovery Act in the US. These firms generate more than 2,200 lbs (1,000 kg) of hazardous waste or more than 2.2 lbs (1 kg) of acute hazardous waste per calendar month.

throughout the figure. The large cluster toward the center of the map shows the area around Boyle Heights and the City of Industry—major industrial centers in the Los Angeles metropolitan region. But the map becomes more difficult to interpret in other areas. For example, there is a large cluster of LQG firms in Orange County (the southern portion of the figure) that does not have a commensurate number of transport spills

Figure 1. Hazmat spills, firms, and major transportation infrastructure



Large portions of the four county area are undeveloped. For all practical purposes, there is little chance of finding firms or spills in those areas, so it would be misleading to include those areas in the analysis. Optimally, the study region would include the developed portions of all four counties in southern California and exclude both interior governmental boundaries and undeveloped land. After plotting the data, I decided to restrict the analysis region to the west of -117 longitude, because of the density of the street development and census tracts; all of the interior boundaries are removed to avoid problems with edge correction in the spatial analysis. All of the spatial analyses in this manuscript are conducted in the open source software, R, although the maps are produced in ESRI's ArcInfo (R Core Development Team 2003).

Cluster analysis

Testing spatial hypotheses follows the same logic as more traditional types of hypothesis tests but uses a different procedure. Exploratory data analysis of both univariate and bivariate spatial point processes usually begins with estimating nonparametric summary measures, such as K-functions to measure spatial dependence (Politis, 2001 #27). Table 3 provides the nomenclature for the equations presented throughout.

Table 3. Nomenclature

Symbol	**Concept**
Z	A spatial process
s	An event in space, a reference point
W	A bounded area in □
λ	The spatial intensity
u	Any point in W not the reference point
N	Count associated with events or variables

r	Distance from s to any other point in W
d	Distance from point to boundary for all
ρ	Scale for facility density
θ_1	Intercept parameter at distance 0
θ_2	Distance-decay parameter

The summary functions alone, however, do not indicate whether the spatial clumping in the data is exceptional in any way. In order to establish statistical significance, these functions are estimated for 1,000 simulations of complete spatial randomness (CSR) of the same number of data points. Complete spatial randomness represents a spatial process in which events in a bounded area W are independently and uniformly distributed throughout the bounded region W, such that:

$$\text{(1.1)} \qquad \Pr(s_o \in w_1, \ldots, s_n \in w_n) = \prod_{i=1}^{N} (|w_i| / |W|); \quad w_1, \ldots, w_n \subset W$$

Because w is a subset of W, the probability that any s appears in w is the same as the product of the ratio $(|w_i| / |W|)$. The likelihood of finding any random event depends on how big w is relative to W, and nothing else. Thus a given event s neither causes nor discourages other events within a predefined distance.

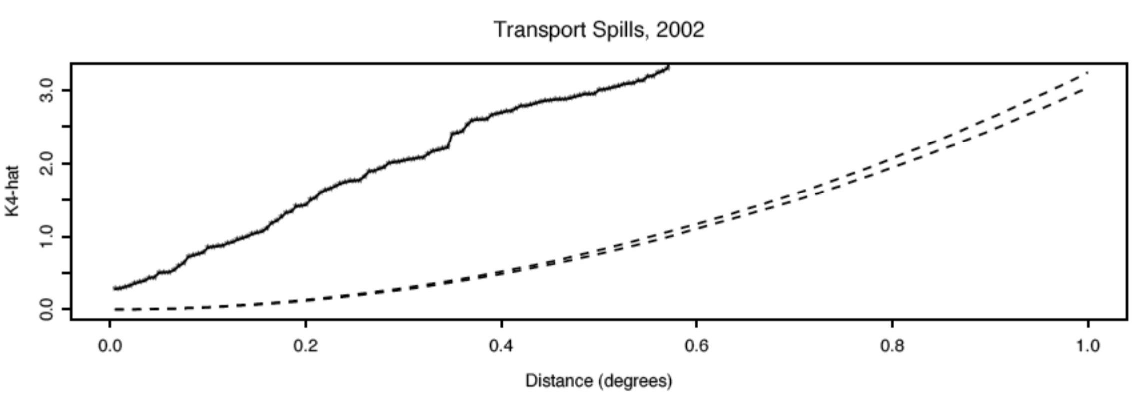
The upper and lower bounds of the distribution from these simulations are plotted along with the functions estimated for the data being tested. The cumulative distribution function for the dataset is plotted against these envelopes. If the cdf of the data falls within the envelopes, it is impossible to reject the hypothesis that the observed data differ significantly from any completely random spatial process. Alternatively, if the function of the observed values consistently falls outside of the envelopes, I can reject the null hypothesis.

An edge corrected test can demonstrate that the clustering exhibited in the data are distinct from CSR. The *K*-function counts the number of events or points within a range of distances of a particular data point (Venables, 1997 #20). Where r is a vector and λ is an intensity, let:

(1.2) $$\hat{K}_4(r) = \hat{\lambda}^{-1} \sum_{i=1}^{N} \sum_{i=1}^{N} w(s_i, s_j)^{-1} I\left(\left|s_i - s_j\right|\right) / N$$

$w\left(s_i, s_j\right)$ is the proportion of a circle with origin s_i and passing through s_j, which is inside the study region (see again (Cressie, 1993 #7)). The results are shown in **Error! Reference source not found.**.

F**igure 2. Khat tests for firms and hazmat spills**



Joint clustering of spills and firms

Bivariate tests can evaluate the co-clustering of facilities and spills. The test is a bivariate analogue of the *K*-function. Hypothesis tests can be applied to two distributions of point locations, such as firm location and spills (Foxall, 2003). The tests are applied to two sets of spatially referenced variables to infer their joint spatial distribution.

The test employs the same methodology as before: the cdf of the distances of the observed variables is plotted against the upper and lower envelope of the simulations. Again, the objective function in begins within the envelopes and then the slope increases quickly. This result makes sense: if the shipment travels some distance off-site before a spill occurs, there may not be a strong local correlation. Nonetheless, the function clearly demonstrates clustering at a larger spatial scale.

Although facilities and spills cluster, it is necessary to establish how many clusters there are, how big they are, and where they are located as well. The clustering indicated in the tests may have resulted from one large cluster or many small clusters. The same is true of the bivariate tests; they show that spills and firms cluster together, but do not reveal where they cluster, how many, or why.

Hotspots

Hotspot analysis can help sort through some of these questions by creating local estimates of the measure of intensity λ.[3] Hotspots count the frequency of points within a given distance of each point, relative to a symmetric distribution. Following Cressie (1993), let $N(s,w)$ represent the number of events per unit area in a $w \times w$ square centered at *s*. Then:

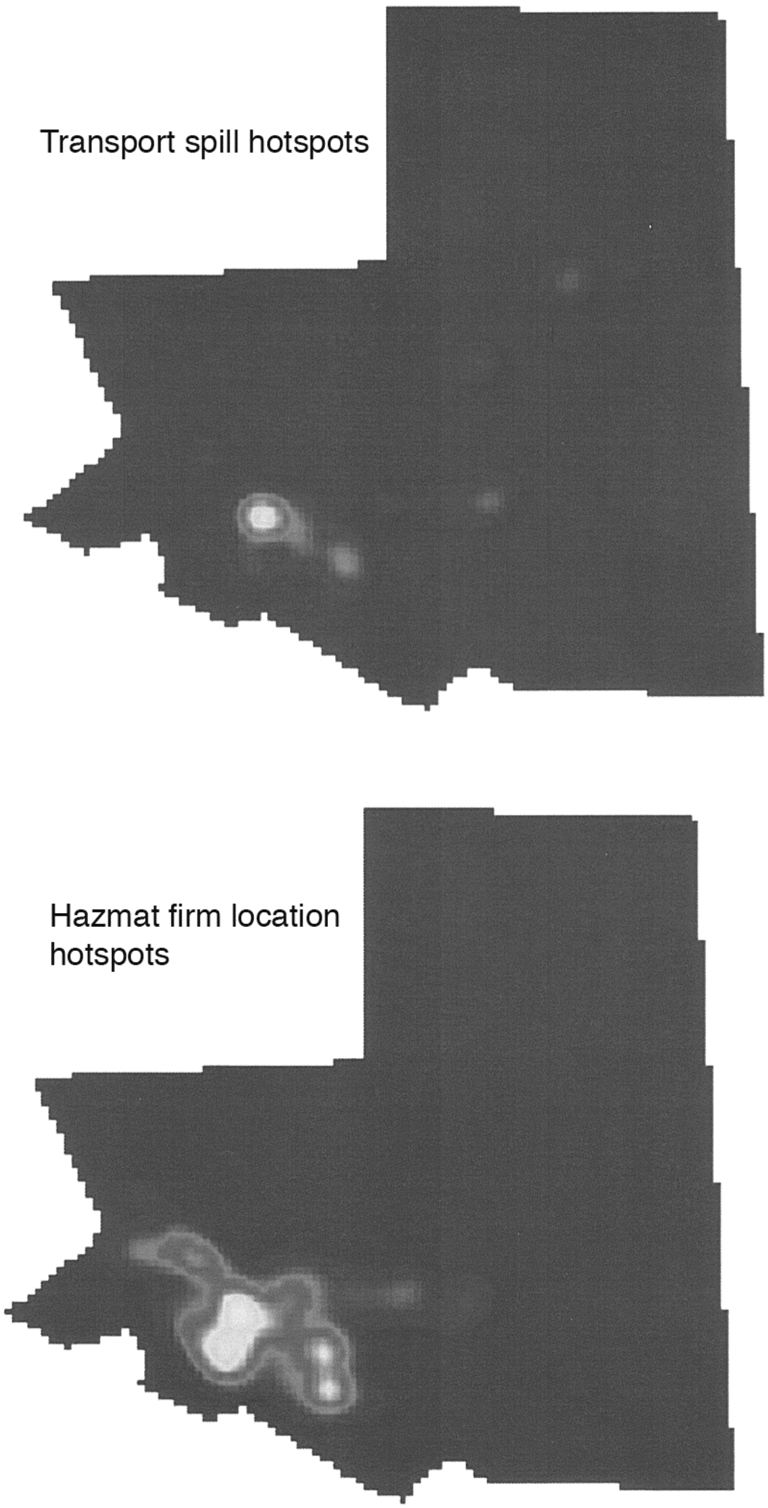
(1.3) $$\lambda_w(s) \equiv \frac{1}{p_d(s)} \sum_{i=1}^{n} \mathrm{K}_d(s-u) \ , \ w \in W$$

This hotspot analysis uses a Gaussian kernel a 0.5-kilometer bandwidth.

The image maps in Figure 3 denote different spatial intensities of event frequencies. The facility hotspots are slightly different yet they overlap with the spill hotspots towards the center of the maps. Again, this exploratory spatial method verifies the environmental justice claim that spills coincide spatially with hazmat firms, but the patterns are not identical by any means.

[3] This procedure is also known as kernel smoothing.

Figure 3. Hotspot locations



Raised incidence model

It would be useful to know whether joint clustering occurs merely because firms and freight traffic occur near or on freeways, or whether firms generate spills nearby. The HMIRS provides shipment origin and destination data, but not routing information. SQL is used to find the subset of the spills within the database that occurred for three different scenarios:

1. Shipments that originated at locations within the four-county region study region;
2. Shipments arriving to a destination within the study region ; and
3. Shipments routed through the four-county area but neither originated nor terminated there (pass-through shipments).

Of the over 4,000 spilled shipments, only about 30 percent were leaving or coming to the four-county area. The third scenario is a subset of the first two; of the 1,467 shipments that are coming or going from the four-county case study, only about 124 were for short-distance trips in the region.

Spills are far more common among shipments coming to Los Angeles than among those on their way somewhere else. But that hardly seems likely. If that were the case, shipments that spill due to improper packing or other human error—the cause of the preponderance of the releases—would have traveled the bulk of a trip only to spill near their shipment destination; that is difficult to believe. A more likely explanation is that shipments destined for southern California spill after they have arrived at an intermodal facility or freight forwarder to be unloaded and loaded for the next leg of the trip. If this is the case, spills due to human error would appear shortly after the shipment transfer.

Specialized freight and intermodel freight firms are likely to locate near major metropolitan industrial agglomerations; there large agglomerations of both freeways, railways, and large industry in LA. Given a large cluster of factories along with the five freeways and railways, Boyle Heights near downtown LA becomes an ideal place for a freight hub operation. The presence of these freight hubs, therefore, may increase the likelihood of spills in and around large industrial areas. A compilation of spill frequency by carrier frequency confirms these suspicions; the top five firms according to spill frequency are all high-volume carriers with intermodal hub operations at several locations throughout the region.

Freight shippers have a prominent presence within the large industrial agglomerations found in Boyle Heights, Commerce, and Industry (downtown Los Angeles). Boyle Heights is a hazmat hotspot due not only to facility or freight density alone, but because both intermodal facilities and freeways (and rail infrastructure) serve large-volume hazmat shippers. Thus, modeling of risk at the regional scale should mark these locations due to their prevalence in the spill record.

Three major assumptions guide the model:

- In this model, spatial proximity between incidents implies no spatial interdependence. In other words, incidents do not cause other incidents.

- Spatial proximity between firms, freight hubs, and incidents does imply spatial interdependence.
- Incident rates calculated along the links can be aggregated to the Census tract. The results of this model have to be interpreted with some caution; aggregate levels should not be assigned to individual road segments without considering the context.

(Diggle, 1990 #8) developed a raised incidence model that treats the intensity of a given phenomenon as a function of distance from a point:

(1.4) $$\lambda(z) = \rho\lambda_2(z)g(r;\theta)$$

where ρ scales the expression for differences in facility density (ranging from 0 to 11 firms per square kilometer, λ_2 is the background or baseline intensity of the process (ranging from 0 to 150 incidents per kilometer), and g is a distance-decay function with parameter θ that represent how spill occurrence changes with distance r from a factory site. If spill occurrence does not increase with proximity, then $g(r;\theta) = 1$. That is the null model. Diggle et al. (1994) offer the following as a functional form for the distance-decay function:

(1.5) $$g(r;\theta) = 1 + \theta_1 \mathrm{e}^{-\theta_2 r^2}$$

The parameters of interest are the θ. θ is an intercept, while θ_2 is the distance-decay effect. Diggle (1990) suggests using a kernel-smoothed estimate of the background intensity, but then in (Diggle, 1994 #30) offer a generalized raised incidence method to avoid the use of kernel smoothing so that additional control points could be included in the model as a multiple. Because I have no control points in the dataset (only spills), a quadrature method is used. A quadrature scheme adds dummy points to the observed data with a mark denoting their status. The dummy points are distributed according to the global intensity of the spills, and act as controls to contrast with the spill locations. Random quadrature points were generated for each year of the HMIRS data because combining years was too computationally intensive. In order to minimize the distortion in distances, the data for both facilities and factories were converted from standard North American Geographic (latitude and longitude) to Universal Transverse Mercator projection.

The parameters are estimated using a maximum likelihood estimation procedure, and the results for each year are shown in Table 4 along with the probability scores of a likelihood ratio test for the θ parameters.[4] The results show that it is possible to reject the null model (1.4). Recall that θ_1 shows the raised incidence around the facility points; it ranges from around 23 spills/km to 52 spills/km—which, when compared with the average of 8 spills/km, makes for a pretty strong case that factories and spills are spatially correlated.

Furthermore, θ_2 controls the distance decay; if θ_2 is large, the model is fitting a large buffer around the facility locations. If it is small, as it is, the model fits a smaller buffer. The empirical tests here show that the raised incidence of transport spills dissipates usually within 2 kilometers of the facility locations.

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[4] All of the analyses in this manuscript were conducted in **R**. The quadrature scheme was developed in the package **`spatstat`**. The cases and controls were exported into **`splancs`**.}

Table 4. Raised incidence models for each year

Year	θ_1	θ_2	Likelihood Ratio Probability
1992	31.02	0.92	0.00
1993	40.10	0.94	0.10
1994	38.92	0.83	0.00
1995	32.32	0.93	0.08
1996	44.23	0.99	0.09
1997	35.92	0.97	0.01
1998	52.23	0.95	0.08
1999	23.90	0.99	0.12
2000	34.63	0.97	0.00
2001	41.47	0.93	0.01

The easiest way to demonstrate the model fit is by comparing the raw and the modeled spill locations, both smoothed. Figure 4 is a smoothed surface of the raw spill rate and the predicted counts from the distance-decay model. The model under-predicts in suburban locations for this particular year. In theory, it is possible to fit a distance-decay parameter for each firm which may better fit the suburban locations.

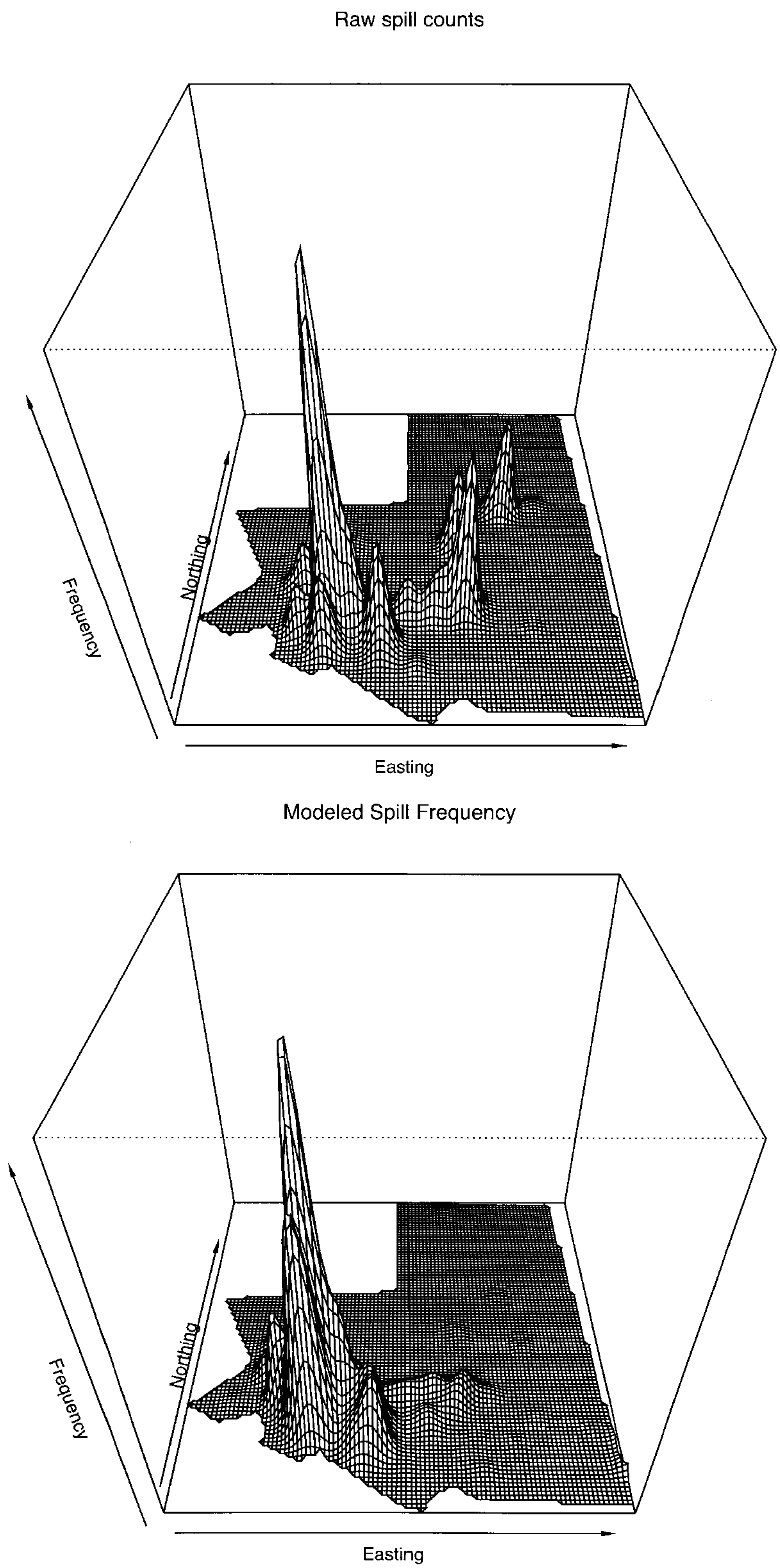


Figure 4. Surface of raw and modeled spill frequency

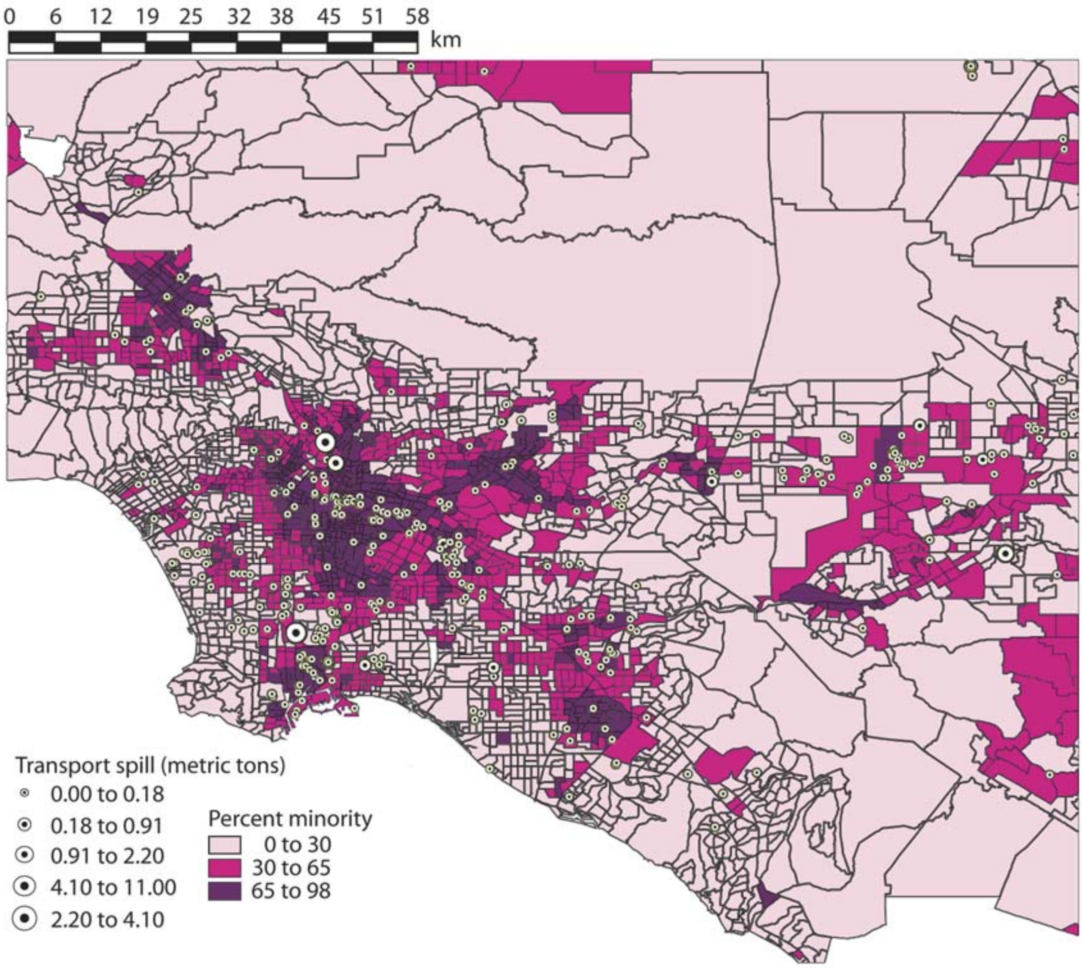
Socio-demographic distribution

Geographic Information Systems assist in the visualization of factory locations, potential risk areas, exposure areas, and socio-demographic variables. For small-scale analysis, US Census Bureau socioeconomic data are used at the Census tract level. To define the minority populations, the Census category P12, Hispanic Origin By Race, differentiates Latino residents from Whites, Blacks, Asians, Native Americans, and Others. The US EPA has suggested various percentage levels to denote areas as "predominantly minority." When environmental justice rules first were proposed, the EPA suggested using 50 percent as the cutoff. More recent guidance from the EPA has suggested that 30 percent, or a percentage that is greater than the minority and/or low-income population percentage in the general population of a city or county.

In examining the spatial distribution of spills according to socio-demographic groups, the number of predominantly Asian tracts is fairly small, though not as small as the number associated with Black or African-American residents of the southern California region. Nonetheless clusters of spills do occur in the Artesia and Long Beach areas where there are also clusters of predominately Asian and Asian American census tracks. Spill clusters occur almost entirely outside of the primarily Black communities, but spills do occur along the periphery. Spills may not occur directly in these communities, but spills follow the freeways near residential areas of Compton, Inglewood, and Watts. The small numbers of tracts associated with small groups are easy to overlook in regression or statistical analysis; yet visual evidence from mapping (not shown due to space constraints) demonstrates that some hazmat spill clusters occur near racial and ethnic enclaves, such as those along the immediate periphery of a Hmong community in Torrance (southwestern part of Los Angeles).

By contrast, Latino residents are nearly half the population in the four-county study area. Figure 5 depicts the spatial correlation between Latino residents and hazmat spills. Because of the large industrial agglomeration, the Latino residents who live in the area surrounding downtown Los Angeles also contend with hazmat spills from these facilities. The frequencies increase with the inverse of distance. Therefore, those who live near the industrial agglomeration must deal with both facilities and spills as well as the nuisance associated with freight traffic.

Figure 5. Transport spills and Latino population, Los Angeles



Stratification scheme 1

The EPA's suggestion that Census tracts or areas containing 30 percent of an ethnic population or alternatively, the use of threshold relative to a city or county base poses some interesting questions for testing risk between groups. A tract containing 30 percent of one minority population can also be comprised of another comparatively large minority group, especially in a place like Los Angeles. On one hand, when a tract is categorized as simply as a "predominately minority" tract, information is lost and the analysis becomes less specific. One way around this problem is to assign the risk to both groups in order to demonstrate how groups share risks. But in hypothesis tests, strata such as these counts some tracts twice between two different groups in the rank and means tests. That practice undermines the assumption that the groups be independent. Therefore, the first approach I use to assign the tract is as follows: for any tract with 30 percent or greater ethnic population, the tract is assigned to the group with the highest percentage; and if more than two minority groups are over 30 percent of the population, the tract is categorized under "None" for no clear majority; these tracts are interesting in and of themselves because they may demonstrate places where neighborhood composition is changing, where residential segregation does not characterize the spatial area, or where the space marks transition areas from one enclave or another. Tracts with over a 70 percent white population were treated as a one group representing the majority. I have omitted other important ethnic groups in Los Angeles because no other groups constituted a sufficiently high number of tracts over the threshold amount.

With skew and uneven group size, groups are not likely to be homoscedastic so that a nonparametric test is necessary. The Kruskal-Wallis procedure is a rank-sum test; the null hypothesis is that the groups are all drawn from a population with the same median. One problem with testing spill counts is that there are sizable outliers in the HMIRS database. One tract, which is predominantly Latino, has over 1,131 small spills during the time period studied. Although the nonparametric test should not be overly influenced by outliers, I wanted to trim the tracts with the very highest frequency to see the maximum counts by ethnic group. These statistics are shown in the second panel of Table 5 where there are statistically significant differences between ethnic groups.

To examine for differences between different groups, Dunn's post test compares the difference in the sum of ranks between two columns with the expected average difference (based on the number of groups and their size). Because of the differences in group size, however, the post-tests were noninformative between Asian Americans and African Americans. However, the post-test for the raw spill counts between Latino and white groups did demonstrate a significant difference; the results for the smoothed and trimmed counts were not significant. Although this stratification method is restrictive, the results show that the tract with the largest number of spills—a sparsely populated but primarily Latino tract near an intermodal facility—appears to sway the test. Ultimately this is a good thing: these types of extreme locations should be interesting to us from an environmental justice standpoint. Even if, on average, Latino residents experience the same number of spills as white residents, the fact that by far the most frequent spill location is located in a primarily Latino tract itself represents an equity (and quality of life) issue worth examining.

Table 5. Kruskal-Wallis Tests of All Risk Measures

Risk Measure	**Kruskal-Wallis Chi-square**	**Df**	**P-value probability**
Stratification Scheme 1			
Transport Spill Count	24.0881	3	0.0002**
Trimmed Spill Count	23.9085	—	0.0000**
Smooth Spill Count	20.2122	—	0.0009**
Stratification Scheme 2			
Transport Spill Count	6.524	3	0.09432*
Trimmed Spill Count	5.212	—	0.101
Smooth Spill Count	3.2122	—	0.279

The results of the first stratification scheme are interesting in one other respect. Although Latinos in Los Angeles have grown to roughly half the population in southern California, they make up the majority population in far fewer census tracts than do their white counterparts; Latinos are more numerous than other groups in 1,619, whites have 2,794. Even though this stratification scheme is rather restrictive (and simplified), it does capture the more space-consumptive settlement patterns of white residents resulting from suburbanization and white flight. In so doing, it is an alternative to regression analyses that do not show how many white tracts, in fact, experience the danger or the nuisance phenomenon under question at fairly high levels, even in demonstrating that firms are disproportationately located within communities of color. But because white metro residents are so spread across space (and others are less so), many white residents have the opportunity to live far from the nuisance which communities of color, much more densely settled, do not have to the same degree.

Stratification scheme 2

A second method of identifying differences in risk disparity is more standard: this method assigns risks to census tracts and then aggregates by group according to the population percentage within the tract. This results in a less restrictive ethnic group assignment, allows for sharing spill counts in a given tract, and provides a more even distribution of observations in each ethnic group. Again, this is done for raw, smoothed, and trimmed spill counts. Table 5 presents the results of the Kruskal-Wallis tests for this stratification scheme. The results are similar, except that the counts are do not appear significantly different for the test on the trimmed spill tracts. However, the counts are significantly different according to raw counts. The smoothed counts, which reflect the levels derived during the hotspot analysis, do not test differently. The post-test shows significant differences between Latino and white groups in the aggregate for raw spills, although this is not a particularly strong finding. At the same time, both sets of tests under both strata are conservative tests meant to account for the skew of the count data; that I find a significant result from these conservative tests provides pretty strong evidence for the conclusion that the spill distribution disproportionately affects Latino residents as a group.

Conclusions

The goal of this analysis is to understand the location risks associated with hazmat transport and factory locations so that planners may better understand how land use and freight transportation variables contribute to the risks that residents associate with factories and freeways. This allows me to draw some conclusions about event risks, if not exposure risks, associated with our land use and transportation decisions.

Simulation-based hypothesis tests demonstrated that transport spills generally cluster near origins more than destinations when we recognize that intermodal facilities represent origins. Using similar methods and an empirical model, the analysis also demonstrated that proximity to origin firms increase spills insofar that large industrial agglomerations attract large freight shippers to serve the surrounding factories. In turn, residents in urban areas near large firm clusters deal with both local and inter-regional hazmat shipments and spills.

How generalizable these particular results are will have to be addressed using additional empirical analysis. Ultimately, few freight transport markets are likely to be as active as those found in Los Angeles, with a major world port that acts as a gateway to and from US and Asian markets. However, the concern over hazmat transport is commonly expressed in the case studies in environmental justice, and thus the methodology and conceptual approach presented here offers a generalizable methodological contribution for planners to use when assessing the interaction between land use and transportation incidents. The first few kilometers after a load or a transfer merit heavier weighting in stochastic models of release probability. Further, residents near origins and transfer points deserve the benefit of the doubt when they argue that they have a higher risk than others living along the line-haul portions of a hazmat route.

While the roadway environment may not be useful for the prediction of routine spills, there are reasons why companies and communities might have a special interest in making predictions about crash-related rather than accidental spills. First, concern over terrorism has increased attention on the possible consequences of stochastic events along the route. Terrorism scenarios can include anything from handheld or small-scale explosives to intentional collisions with hazmat trucks or railcars. If the evidence from this analysis holds in other locations, the routing of hazmat traffic, the potential for terrorism, and the possible actions to address perceived terrorist threat could have distributional consequences on those who live near hazmat routes and origins.

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