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Accident frequencies in environmental justice assessment and land use studies

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Abstract

Environmental justice advocates in the US and internationally have argued that hazardous materials industries are a source of significant community disruption and environmental hazard. Few of these studies, however, have examined firms' accident frequencies or how accidents are distributed across metropolitan regions. This research argues that accident frequencies differ significantly among firms, and they are an important part of understanding industries and their distribution within metropolitan regions. The accident records of the risk management plan (RMP) facilities in southern California provide an illustration for the discussion. Statistical tests demonstrate that previous accident counts correlate with future counts. The research heightens the usability of the existing accident record for local governments in the US.

Keywords: Accident frequencies; Land use planning; Environmental justice

1. Introduction

In recent decades, technical risk assessment as a process has become contested as communities resist the nearby location of new industrial land uses, and increasingly, question the safety of existing industry. Environmental justice advocacy and research have demonstrated that polluting facilities are clustered geographically near impoverished communities and communities of color [1–4]. In studies of environmental injustice and land use, analysts have been primarily concerned with the geographic location of polluters relative to residential populations by race, class, and ethnicity [2,5–14]. The authors within this field of research assume, for the most part, that facility locations provide a good proxy for where toxic and hazardous emissions occur in urban geography. The practice reflects the information limits for analysts working at the regional scale, as full risk assessments are seldom available for all the hazardous materials firms within any given US region.

However, past accident frequencies and consequences are also available to those who wish to examine environmental injustice. Large-scale disasters, such as those that have occurred at Bhopal, Chernobyl, Mexico City, Enschede, and Toulouse serve as reminders that accidents can endanger nearby populations in addition to the everyday, chronic emissions that can come from nearby polluters. Major accidents are infrequent and difficult to predict, but in this manuscript I demonstrate that the accident rate from 1987 to 1995 is a strong correlate of the accident rate from 1995 to 1999 in the Los Angeles region. Thus, past accident rates are reasonable predictors of future accident rates. The empirical data record on accidents can further be used to construct statistical distributions of accident frequencies for individual facilities. With these distributions, it is possible to create a space-time geography of accident frequencies which can then be mapped along with human populations for land use studies and by race, class, and ethnicity for environmental justice assessment. These can also be weighed against potential consequences to derive a simplified understanding of industry within regions.

Throughout this manuscript, I present the accident and regional data for four counties in southern California in the United States: Los Angeles, Orange, San Bernardino, and Riverside counties. There are large differences in the accident frequencies among refiners in southern California during my case study time period from 1987 to 1999: Mobil had 21 accidents with recorded off-site consequences; Unocal had 18, Ultramar 16, Texaco, Shell 7, Chevron 10, and Arco 23. These refineries are located in and around Torrance, Carson, Wilm-

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ington, El Segundo, and Long Beach in southern California. How should local government officials and community members regard these differences in the number of past accidents? As simple artifacts of stochastic processes? As proof some refineries are better than others at containing spillovers from their processes? A sign that perhaps residential land uses and roads are growing too close to some, or all, of these facilities?

To be clear, I do not suggest accident frequencies as a replacement for risk assessment; nor do I advocate ignoring accident consequences in analysis. Past accident frequencies are an imperfect proxy for probability, and they do not capture consequences. However, data availability often makes using formal risk assessments or modeled accident consequences infeasible for regional geographic analysis. Major accidents are infrequent; breaking major accidents into particular consequences makes the events through time even more sparse and, therefore, nearly impossible to test for patterns in time or geography. Rather, in this manuscript, I analyze the frequency of all accidents that have had off-site consequences. Even if imperfect, regional analyses of environmental injustice and future land use decision-making benefit from accident information, even when it is approximate, regarding where accidents have been more frequent within a metropolitan region.

2. Why accident frequencies?

Reduced to a simple-minded characterization, risk assessment weighs the probability of an accident against the potential consequences: from there, a spectrum of risk representation emerges where high probability, high-consequence events portend greater potential problems than low-probability, low-consequence events, and so on. Accident frequencies enter into probability calculations: how often something has happened in the past qualitatively reveals something about its probability.

As we examine the previous data record, research has demonstrated that it is possible to use the number of small accidents as predictors of major accidents at industrial sites [15]. Even with over a decade of data on major accidents in the United States, this area of analysis is hampered by the sparseness of the data record and the comparatively low frequency of major accident events. Based on the existing data, it is very difficult for local communities to discern whether a facility has never had a major accident because (a) the processes are straightforward, the onsite safety culture is exemplary, or the processes and materials are comparatively safe or whether (b) none of the former is true, but nothing has, thus far, resulted.

In the Los Angeles region, 121 members of the public were injured in the Los Angeles region in major hazardous materials incidents. All of these injuries occurred in four releases. In fact, two releases were responsible for over 100 injuries. On 11 November, 1990 at 9:00 in the morning (rush hour), 98 pounds of hydrogen sulfide gas escaped from the Shell refinery in Carson, injuring 60 members of the public. The second largest number of injuries, 49, happened as a result of a sodium hypochloride release from Happy Health Spas in Torrance in November 1991.

These two incidents provide an interesting contrast based just on the data record. The Shell refinery is a large facility holding large amounts of comparatively volatile chemicals and onsite staff. In contrast, Happy Health Spas appears in the data record only once. Unlike the professional materials specialists (usually engineers) listed as the contact person for most releases in the accident record, a secretary at the Happy Health Spas is listed as the main facility contact. Also, the first response listed in the data was to call 911 rather than engage in on-site first response, which suggests the facility staff and management were not trained for on-site measures.

A firm's accident record demonstrates both something about the hazardous nature of processes and materials and the firm's capacities and practices. While fault-tree and other *ex post* analyses can reveal much about what happened to cause these accidents, the most serious release events in the recent history of Los Angeles demonstrated really different institutional contexts—things that outsiders to the industries can be expected to know little about, except from industry and government reports. For outsiders, the rigor and integrity of information from industry represents yet another source of uncertainty.

Process safety specialists have derived methods for comparing accident frequencies, and it is possible to see if a given facility is outside the industry norm [16]. But for planners and environmental justice advocates, where accidents occur is a very different question than explaining why a given facility has the accident record it has. Rather, these groups seek reasonably accurate geographic representations of hazardous materials, and what the urban geography tells us about the potential space-time connections between hazards and human populations. This type of information, while imperfect, creates a fuller understanding of how problems are distributed among groups and across urban geography, particularly for those who do not have access to the same level of data or expertise – or trust in experts and their data – that industries and regulators do.

Given the issues about information quality, outsider analysts face some tough choices. They can attempt to generalize across industries (i.e. the average rate per unit operation time of major accident events), or they can generalize across facilities within a specific industry (i.e. the accident frequency per unit operation time among petroleum manufacturers). Another option is to use the empirical record even though it counts only places where accidents have happened. Researchers on environmental justice have used primarily spatial measures to locate where industry is and what it has done, including the everyday consequences of operations and the consequences of extreme events. The locations used in these analyses tend to be static, marked solely as locations or location points marked with emission volume data. A perhaps more productive approach would be to reflect event uncertainties – without necessarily trying to explain them – based on the empirical data record throughout urban geography.

2.1. Local accident data

In order to take a look at major accidents – accidents that have caused injuries, evacuations, or deaths outside of the facility – I use two datasets from the U.S. Environmental Protection Agency: risk management plan data and accidental release inventory program data. The clean air act amendments of 1990 mandated risk management plans. These amendments required the EPA to establish regulations and handling guidance for facilities that might have potentially high off-site consequences, such as those that handle extremely hazardous substances or very high volumes.

The act requires that RMPs outline the type and volumes of material used in industrial processes, the potential effects of an accidental release, and the facility's emergency preparation. While the region has over 12,000 facilities holding hazardous materials permits of various types, only 178 facilities in Los Angeles County had to prepare RMPs. Orange County had only 36, while Riverside and San Bernardino Counties had 52 and 56, respectively.

For homeland security reasons, access to much of the information from the most recent RMPs was limited primarily to agency researchers at the time of this writing. The EPA classifies the modeled off-site consequences, so that those are unavailable for outside researchers and community members. Therefore, information about plumes or possible exposure areas were not available. However, the facilities' five-year accident records were available, including data on those accidents that caused off-site injuries, deaths, and evacuations.

Also, Fig. 1 displays some of the facilities' data. Volumes are shown in histograms, rugplots, and the empirical cumulative distribution function (ecdf). The ecdf or empirical cumulative distribution of a sample, $Fn(y)$, is the proportion of observations less than or equal to (y). In Fig. 1, the top histogram and ecdf refer to the entire dataset. Because of the extreme skew in the distribution, it is difficult to glean any information about the firms handling less than 200,000 pounds of materials.

To address this problem, the second row of graphics in Fig. 1 displays the distribution of the data for firms handling less than 200,000 pounds of a substance (the first category in the first figure). Even in this subset of the data, the distribution is skewed toward the lower values. The distribution of the subset is only slightly less skewed than for the complete data set. This distribution is common among virtually all of the volume variables and datasets.

Table 1
Information in the ARIP database

Date/time
Quantity released
Medium affected
Costs (facility or public)
Deaths
Injuries
Release duration
Environmental damage
Type of release
Location of release
Cause
Number evacuated or sheltered
Agencies responding
Chemical name

Among the RMP firms, most handle only one chemical in large volume; 113 firms handle high volumes of chlorine, while 70 handle ammonia. Thus, the RMP data describe facilities with some information on accidents. By contrast, the US EPA compiled the accidental release information program (ARIP) database in order to identify the causes of accidental releases. In order to gather the ARIP data, the EPA examines data from the emergency response notification system (ERNS) for on-site releases that either resulted in causalities, off-site consequences, or environmental damage. The data are organized by spill, not by facility, but the facilities have good address information. The EPA has collected ARIP data since 1987.

Table 1 contains a summary of the most relevant data. From 1986, the ARIP data were collected on releases that caused death or injury; involved 1000 pounds or more of a hazardous sub-

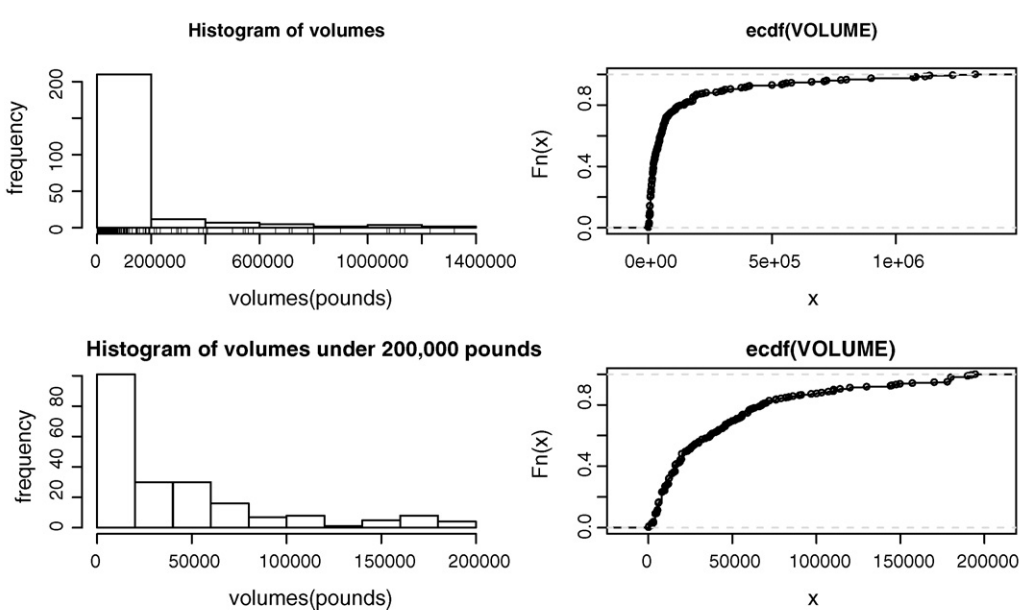

Fig. 1. Chemical volumes at RMP Facilities.

stance with a reportable quantity (RQ) of 1, 20, or 100 pounds, or the release involved 10,000 pounds or more of a hazardous substance with an RQ of 1000 or 5000 pounds; was the fourth through the tenth release in a 23-month period; or involved an extremely hazardous substance according to US hazardous materials regulations.

The ARIP data record all the off-site consequences associated with the releases. During the 12-year time period, there were no fatalities among nonemployees reported in the ARIP database. There were, as mentioned earlier, 121 injuries. Less serious than injuries to the public, but disruptive and troubling to communities nonetheless, are evacuations and shelters due to industrial activities. From 1987 to 1999, 1551 people were evacuated because of on-site hazardous materials releases in Los Angeles. One incident accounted for 1000 out of the 1551 people who were counted as evacuees.

On the one hand, the risk management plan data marks those facilities that, according to regulatory agencies, represent possible sources of serious off-site consequences. By contrast, the accidental release information program data records serious releases that have actually occurred. Using the risk management plan data alone in the analysis would limit release information to the last 5 years. The risk management plan data report facility operating characteristics but not much about accidents. Similarly, the accidental release information program database describes accidents, but very little about the facilities themselves. For this analysis, I therefore use the two datasets together with caution. By applying event data (ARIP) to the facilities data (the RMP data), it is necessary to assume that the accident frequencies will reflect improvements that occur in safety over time, all else equal.

2.2. Simple frequency models

If the available inventory of major releases may not cover a sufficient time period to derive the accident rate (Λ) due to the comparative infrequency of major spill events, then a Bayesian approach makes sense. The accident or hazard rate can be theorized as a point process in time, such as with hazard models. Hazard regression models are widely used in medical insurance, employment, and accident analysis research. The models are designed specifically for analyzing time-to-event data, like accidents. Table 2 provides a definition of statistical terms for those who may not be familiar; Table 3 is a summary of the nomenclature used throughout the manuscript.

It is possible to define the time-to-accident release as $(t_i, \delta_i, x_i)\,\forall i = 1, \ldots, n$, where t_i is the observed time without an accidental release, δ_i a censoring variable (like a spill), and x_i is a vector of coefficients associated with facility i. In the case of a firm's accident frequencies, a_i denotes a string of time without an accident event, and c_i represents the random time at which the data are censored in time. Then,

$$\delta = 1, \quad \text{when } a \leq c$$
$$\delta = 0, \quad \text{when } a = c \text{ or when } t = a$$

For a particular facility, a denotes a string of time without an event, and c represents the random time at which the observations are censored. These discrete units of time allow me to further define the problem, accident frequency, in terms of events per unit time, with $N(t)$ as the number of accident events up to time t, dt as a small increment of time, and $o(\mathrm{d}t)$ as a much smaller partition of dt such that $o(\mathrm{d}t)/\mathrm{d}t \to 0$ when $o(\mathrm{d}t) \to 0$. Thus,

$$N(t+\mathrm{d}t) - N(t) = \begin{cases} 1, & \text{with probability } \lambda(t)\mathrm{d}t \\ 0, & \text{with probability } 1-\lambda(t)\mathrm{d}t \\ >1, & \text{with probability } o(\mathrm{d}t) \end{cases}$$

$N(t+\mathrm{d}t) - N(t)$ is simply the number of events that occur between t and $t+\mathrm{d}t$. This formulation comes from work done by Pawitan [17]. The goal is to derive a likelihood associated with a given accident rate for a given facility that approximates the true rate (λ), and the distribution of accident rates. The estimation

Table 2
Guide to statistical terms

Term	Definition
Bayesian	Approach based on the theory that past event data can be used to update or infer probabilities
Cox proportional hazards model	Model used to describe how an event occurs over time
Gelman and Rubin Test	Test statistic that indicates whether MCMC simulations have converged on a stable distribution
Gibbs sampling	An algorithm that repeatedly generates samples from a joint probability distribution; an MCMC method
Maximum likelihood estimator	Method used to fit model parameters
Monte Carlo Marko Chain	Algorithm for repeatedly sampling from a probability distribution
Partial log-likelihood function	Method for maximum likelihood estimation
Posterior distribution	The distribution that results from multiplying the prior distribution times the likelihood function
Prior distribution	Distribution that describes existing beliefs about the phenomenon
Spearman's ρ	A nonparametric test of correlation

Table 3
Nomenclature

Symbol	Definitions
t	General definition of the time that elapses between events at a particular firm: time measured in months
δ	Event that marks an interruption in the glow of time without accidents
a_i	Time without an accident for a given facility I
c_i	Accident event at a given facility i
Λ	"True" accident rate
λ	Coefficient estimates on variables X
X_i	Vector of variables X
h	Computed hazardousness measure
$R(t_i)$	Baseline frequency; mean frequency, industry rate, or rate derived from desired percentile

for the accident frequency follows the following model:

$$L_i = p(t; X_i) = \prod_{i=1}^{n} \left\{ \frac{\exp(\beta^{\mathrm{T}} x_i)}{\sum_{j \in R(t_i)} (\beta^{\mathrm{T}} x_j)} \right\}^{\delta_i} \quad (1)$$

where X_i is a vector of covariates associated with a given facility i at time t. Eq. (1) is a common form of the Cox proportional hazards model [18]. Note $R(t_i)$. This is a baseline accident frequency per unit time, applied to all facilities that hold hazardous chemicals, and it is the mean frequency for all facilities in the sample (0.0012). All frequencies in this analysis are calculated according to month and then multiplied by a thousand to avoid the clutter of scientific notation. With including this measure, the overall model of frequencies will overpredict the accident rate. Here, β represents a vector of regression parameters, which does not include an intercept. Rather, the baseline hazard is covered by $R(t_i)$. L_i is always positive due to the exponential functional form.

The covariates contribute to location frequency exponentially rather than additively. The MLE estimators of β are obtained via a partial log-likelihood function. The MLE estimates of β are obtained by maximizing the partial log-likelihood function $l(\beta) = \ln L(\beta)$. Formally stated, maximize:

$$l(\beta) = \sum_{n=1}^{n} \delta_i (\beta^{\mathrm{T}} x_i) - \sum_{i=1}^{n} \delta_i \ln \left\{ \sum_{j \in r(t_i)} \exp(\beta^{\mathrm{T}} x_i) \right\} \quad (2)$$

2.3. Covariates

There are limited data available for facilities, and the data available are often difficult to combine across facilities because different chemical and different processes are so unique. However, the descriptive analysis revealed that a couple of variables correlate with previous spills recorded in the accidental release information program data and the risk management plan data.

One of these potential factors (x_i) is facility hazardousness. It is difficult to compare different types of industrial chemicals because the volumes and the hazards they pose are so different. Elliott et al. [19] created a rank measure of hazardousness for their environmental justice study. The measure is intended to better reflect differences in manufacturing scale and hazardousness. They create a variable that reflects both the volume and threshold level of the materials handled or stored at each facility:

$$h = \begin{cases} 0, & \text{if chemical is kept at threshold levels;} \\ 1, & \text{if chemical is kept at twice the threshold levels;} \\ 2, & \text{if two or more chemicals are kept at twice the threshold level; or one chemical is kept at four times the threshold level} \end{cases}$$

Threshold scores were calculated for the 296 facilities of the risk management plan database. The threshold levels for each regulated chemical are inversely proportional to the hazardousness of the chemical, as measured by volume or weight. Clearly, this is a convention and an approximation. Not all hazards are readily understood according to amounts. Nonetheless, the h measure provides a useful way to begin exploring a facility's frequency as a function of the volume and type of materials on site. In calculating h, several facilities in Los Angeles did not fit well into this measure, such as the petroleum refineries. These may use far more than two chemicals or may use three or four chemicals in numerous combinations and in multiple processes. Another major facility poorly represented using h is an intermodal storage facility in San Bernardino. This facility stores well over fifty chemicals in various forms in high volumes. The potential hazardousness from the facility – to the extent that h is a measure of hazardousness potential – can be understated using this simple measure.

Table 4
Variables for frequency model

Betas	Variables (X_i)	Range	Mean	Spearman's ρ
β_1	Previous reported spills[a]	1–21	0.0235	0.7748**
β_2	Full time employees	4–6700	982.9	0.03
β_3	Hazard score[b]	0–2	0.832	0.4548**
β_4	Number of operations	1–5	1.22	0.7048**

** Significant at 0.001.
[a] Data compiled by the author from Accidental Release Information Program Data.
[b] Data compiled by the author from Risk Management Program Data.

The spill count per month for 1995–1999 is the dependent variable. Table 4 summarizes the list of variables tested as correlates. A history of spills from 1987 to 1995 had the highest correlation with spills from 1995 to 1999. Two other possible correlates may similarly be good predictors of empirical count of spills reported: (1) the number of full-time employees (FTEs) and (2) the number of industrial processes on-site. Both could be proxies for firm size or professionalism; FTEs might reflect differences between firms, such as the Happy Health Spas example, where fewer FTEs reflect a paucity of onsite professional staff. However, FTEs had no significant correlation. The hazard score and the number of operations were both correlates, but they correlate with each other more than either correlate with the accident rate. The strongest correlate of future accidents are previous accidents.

The data included in the likelihood model are those significant results from Table 4: previous spills and hazard score. The number of operations could be used, or the just the previous accident rate. The priors for the coefficients are assumed to derive from the uniform distribution. The samples were drawn using a Gibbs sampling algorithm in WinBUGS [20]. The Gibbs method samples any one of the variables conditioned on the others. MCMC chains, as part of the Gibbs sampling method, simulated over 7000 iterations, and the first 1000 are discarded to allow for the chains to converge. The simulations were tested for convergence using the Gelman and Rubin test with the CODA software.

The resulting distributions for per-month frequency for the high-probability facilities can be contrasted with low probability facilities. Fig. 1 shows a sample of boxplots of the estimated frequency distributions for selected facilities. Due to space constraints in the graphic, the firms are lettered. Parameter estimates illustrate the considerable uncertainty associated with the frequencies. Nonetheless, differences in the frequency distributions emerge between facilities; these are differences that can be mapped through time and space. Some have an empirical track record that indicates they have had problems in the past. It does not mean they were negligent, and it does not mean that firms that have not had accidents yet will never have one. But it does show that stable distributions emerge, given that accidents are fairly decent predictors of future accidents. A city could do worse than look at past accident locations as a proxy for where events are comparatively more likely within the region in the future (Fig. 2).

In looking at the simulated distributions, the mean consistently overpredicts accident frequencies for facilities that have had no accidents (due to the inclusion of a baseline). The mean frequency from the simulations tends to underpredict for only 7 out of the 176 firms analyzed with these data. If the analyst wanted to pursue a strictly precautionary rate, it might make sense to go with the value associated with the 90th percentile, all of which overpredict the empirical rate from 1994 to 1999. Any point in the calculated distributions may be matched with other data, as in Fig. 3, which maps mean frequencies for the risk management firms in the four-county area.

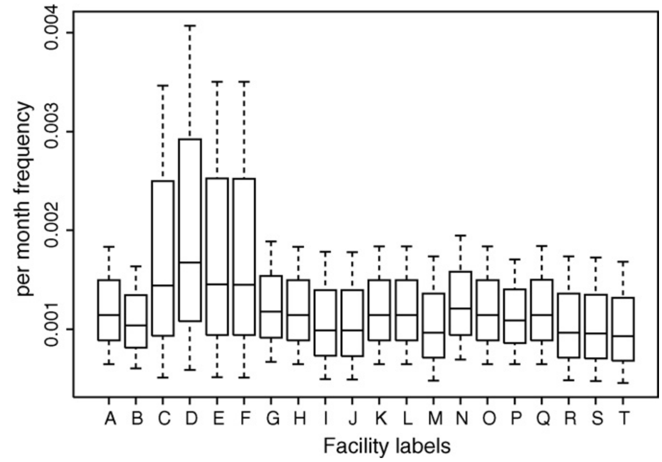

Fig. 2. Frequency distributions for a selection of both high- and low-frequencies firms.

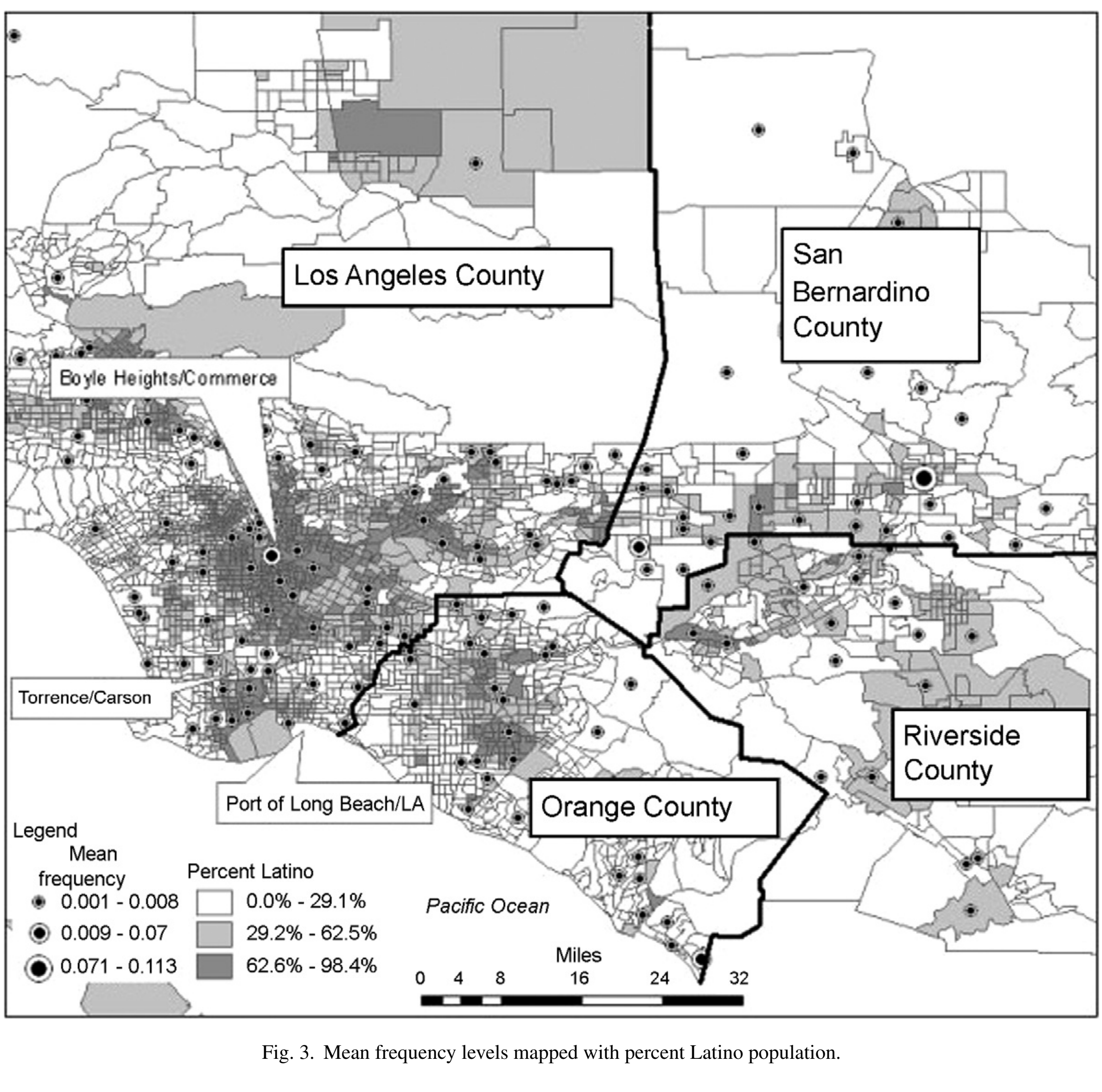

Fig. 3. Mean frequency levels mapped with percent Latino population.

Clear geographic and, therefore, socio-demographic differences emerge in this map—a useful addition to comprehensive planning discussions about either environmental justice or future land (re)development plans. Los Angeles has been studied perhaps more than any other region in studies of environmental injustice [21]. Those studies consistently highlight a show a large cluster of hazardous materials handlers in the Boyle Heights/Commerce/Industry areas Los Angeles. The high-consequence and high-frequency firms from the RMP data are far less clustered. Although there is one high frequency firm in the Boyle Heights/Commerce/Industry area, there are two high-frequency, high-consequence firms in suburban San Bernardino that previous environmental justice studies have not discussed.

Based on these calculations alone, those outside the industries cannot tell if the high frequencies associated with the two firms in San Bernardino are due to high frequencies from the state of the practice in those industries, which I will not disclose to honor security goals. We also cannot tell whether these frequencies are due to ongoing problems at the facilities. Their differences are, however, meaningful descriptions as municipalities and local communities consider future land use decisions surrounding those firms.

3. Closing remarks

This analysis illustrated how simulated distributions should nudge land use studies and environmental justice efforts in the US into greater awareness of the differences in facility accident performance over time. It is designed particularly to illustrate the usefulness of estimating distributions to understand the mean and upper and lower frequency values for accident probabilities in mapping facilities throughout metropolitan regions. These geographic, time-based estimates may be particularly useful for especially those in the US who have ready access to prior accident data, but little access to full risk assessments for the facilities in their regions.

Simple models and correlation analysis demonstrated how even though such accidents are rare, past events are a respectable if partial predictors of future event locations. If outsiders to the industry are looking for simplistic proxies for how industries and their associated characteristics manifest within the urban geography, they could do worse statistically than to use where accidents have happened in the past. In addition, the consequences of these past accidents similarly contribute to a fuller, if simplified, understanding of the urban geography of major accidents.

For those who want to understand the geography of hazards, history matters as well as geography. US local planning organizations have not typically had the institutional ability to pursue, retroactively, greater land use buffers between industries and human populations. The results that I show here give localities a partial empirical justification for pursuing performance-related buffers for industries within the rubric of land use planning. As metropolitan regions have experienced high levels of population growth and competition for scarce housing and land, pressures to develop land near existing industries have increased. A strong push in sustainability and land use planning similarly argues for redeveloping industrial land, which may place residences and commercial areas closer to the high-consequence, high-frequency facilities I examine here than many outsiders to industry may realize unless infrequent events are studied.

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