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# Self organized hotspots and social tomography

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## Abstract

A social network often has numerous interesting attributes. When an attribute is quantified, a social tomography would arise from the underlying social network. One of the most interesting attributes is crime hotspots, whose existence has been strongly supported by observations that serious crimes ranging from residential burglary to homicide are strongly patterned in time and space, and by mathematical modeling. So far, however, the structures of hotspots, including their size distributions, have not been adequately studied. Here, we focus on a special type of hotspots, the sex offender clusters, in the United States, and show that their size distribution, where size is defined as the ratio between sex offender population and total population in a 5-digit zip code area, follows a power-law distribution. In contrast, such local total population, both general and sex offenders, do not quite follow power-laws. A heavy-tailed power-law distribution is fundamentally different from a thin-tailed distribution such as a Poisson distribution, and can be used as an objective criterion for defining sex offender clusters. More fundamentally, a power-law is a defining property of self-similarity or fractal behavior. Therefore, our finding indicates that sex offender clusters, size-wise, self-organize into a fractal, due to interplay of economic conditions of offenders, policies and public perceptions.

**Keywords:** social tomography, crime hot spots, sex offender clusters, power-law distribution

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## 1. Introduction

Imagine driving through a good-sized city and pass through many unmarked safe and not-too-safe neighborhoods. At the turn of a corner, we may find ourselves in a very different neighborhood from where we just left a moment ago. While a city may have a flat physical layout, different neighborhoods may possess very different "tomography", with "health" and "cancers". Structure in a social network with complex tomography may not be flat or benign, but could be dangerous. When geo-spatial layout couples with sociology, the concept of social "tomography" can provide significant insights into the underlying structure and potential impact of the network. An important aspect of social tomography is crime hotspots.

It is well-known that serious crimes ranging from residential burglary to homicide are strongly patterned in time and space forming the crime "hotspots" [1–3]. Their existence recently has further been demonstrated by mathematical modeling [4–6]. Few studies, however, have researched the general structure of hotspots, such as their size distribution. In fact, the size of hotspots given by mathematical models is more or less fixed [4, 5]. To gain a deeper understanding of the structure of hotspots, in this work, we focus on a special type of crime hotspots, the clustering of sex offenders in different states of the U.S.

Recent estimates by National Center for Missing and Exploited Children indicate that there are nearly 603,000 sexual offenders registered in local, state and federal databases in the U.S. [7]. Furthermore, about 60,000 – 70,000 arrests are made each year in the U.S. for charges of child sexual assault [8]. With the increasing public awareness of sexual offenses, there has been strong public support for *community notification* as well as *residence restrictions*, two legislations that provide, respectively, information to communities regarding released offenders [9–12] and limit

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the locations where sex offenders can reside [13–16]. The rationale behind these policies and the support they have been receiving can be partially attributed to the perception that sex offenders may recidivate.

Community notification and residence restrictions have resulted in housing difficulties for many sex offenders. As a result, many of them have to live in cheap, disorganized, deprived, and segregated communities [17, 18], a phenomenon that is suggestive of sex offender clusters [19–21]. This is a very troublesome phenomenon — if sex offenders are truly clustering, then rehabilitation efforts targeted to convicted offenders may not have much success; even worse, communities with sex offender clusters can become highly problematic or intimidating neighborhoods. To aid policy makers, correction agencies and local law enforcement officials in developing suitable policies to mitigate sex offender clusters and ensure environmental fairness for offenders while protecting innocent women and children, it is important to develop objective and effective means of determining whether sex offenders are truly clustering.

Clustering can be studied by a variety of methods, including excellent models such as complex networks [22, 23] and neutral clustering [24–26]. In crime study literature, Poisson statistics have been widely used, and deviations from the Poisson model may be used to define a hot spot[27, 28].

In this work, we ask a fundamental question: in what way do the underlying statistics of sex offender data deviate from a Poisson model? In searching the answer, we naturally come up with a new and more quantitative way of determining whether sex offenders are clustering.

More importantly, we can now answer whether sex offender clusters within a state may have an overarching organizing principle.

For our purpose, we examine four states, one is New York, to represent the East coast, another is California, to represent the West coast, and two more are Illinois and Ohio, to represent the Midwest. We show that the distribution of the size of sex offender clusters, where size is defined as the ratio between the sex offender population and the total population in a five digit zip code area, follows a power-law tail. The start of the power-law tail defines objectively a threshold value, below which, a zip code area is classified as normal, while above which, a zip code area is classified as containing a sex offender cluster. A power-law distribution is fundamentally different from exponential distributions. The prevalence of power-law distribution thus underpins the deviation from Kulldorff's Poisson process based spatial scan statistic [28]. More importantly, a power-law is a defining property for self-similarity or fractal behavior [29]. Therefore, the existence of power-law size distribution for sex offender clusters signifies that sex offender clusters, size-wise, self-organize into a fractal, due to interplay of economic conditions of offenders, policies and perceptions.

## 2. Materials and Methodology

The sex offender data for Ohio, New York, and California were obtained from the National Sex Offender Public Website [1], while those for Illinois were obtained from Illinois Sex Offender Information [2]. The total population data for the four states were obtained from U.S. Census Bureau [3]. We have discarded problematic data entries, including those with zero population or those with sex offender population equal to or greater than the total population. The basic statistics of the data are summarized in Table 1.

Kulldorff's spatial scan statistic for identifying a hot spot or cluster is based on maximizing deviations from a Poisson distribution [28]. Poisson distribution, like exponential and Gaussian distributions, belongs to the so-called thin-tailed distributions, whose moments are all finite. The opposite of the thin-tailed distributions is called heavy-tailed distributions. It is described by

$$P[X \geq x] \sim x^{-\alpha}, \; x \to \infty \tag{1}$$

where $P[X \geq x]$ is called complementary cumulative distribution function (CCDF). When $\alpha < 2$, the variance and all moments higher than the second-order are infinite. Furthermore, when $\alpha \leq 1$, the mean also diverges. When an arbitrary number of random variables with infinite variance (i.e., $\alpha < 2$) are summed together, the distribution for the summation is not a Gaussian random variable with a finite variance, but is a random variable still with infinite variance — the limiting distribution is called an $\alpha$-stable law (this is the generalized central limit theorem; see Chapter 7 of [29] for details).

In this study, we test whether any statistics of sex offenders can be described by a heavy-tailed distribution. If yes, then obviously the statistics for sex offenders deviate from those of Poisson, and it has to be concluded that sex offender clusters indeed exist. Specifically, we consider all $n$ 5-digit zip code areas of a state. Denote the population in the $i$-th zip code area by $p_i$, and the population of sex offenders in the same area by $s_i$. We shall examine whether $\{p_i, \; i = 1, 2, \cdots, n\}$ and $\{s_i, \; i = 1, 2, \cdots, n\}$ follow heavy-tailed distributions. More importantly, we shall examine if their ratio, which may be called raw risk,

$$r_i = s_i / p_i, \quad i = 1, 2, \cdots, n \tag{2}$$

follows a heavy-tailed distribution. For later convenience, we define two more quantities:

$$r_0 = \frac{\sum_{i=1}^{n} s_i}{\sum_{i=1}^{n} p_i} \tag{3}$$

[1] http://www.nsopw.gov/Core/OffenderSearchCriteria.aspx?Advanced=1
[2] http://www.isp.state.il.us/sor/sor.cfm
[3] http://factfinder.census.gov/home/saff/main.html?_lang=en

| States | New York | California | Illinois | Ohio |
|---|---|---|---|---|
| Total population | 18,975,844 | 33,863,571 | 12,214,709 | 11,353,002 |
| Offender population | 20,663 | 38,036 | 13,037 | 19,205 |
| Number $n$ of 5-digit zip code areas | 1,602 | 1,667 | 1,072 | 1,160 |
| Population ratio $r_0$ | 0.0011 | 0.0011 | 0.0011 | 0.0017 |
| Mean ratio $\bar{r}$ | 0.0017 | 0.0039 | 0.0021 | 0.0019 |
| Threshold $r^*$defining the start of power-law | 0.0022 | 0.0013 | 0.0018 | 0.0020 |
| $\alpha$ exponent | $1.70 \pm 0.05$ | $1.25 \pm 0.05$ | $1.66 \pm 0.06$ | $1.89 \pm 0.04$ |
| Number $C$ of sex offender clusters defined by $r \geq r^*$ | 361 | 669 | 388 | 361 |
| ratio $C/n$ | 22.5% | 40.1% | 36.2% | 31.1% |

**Table 1.** Basic statistics for the data studied here; $r_0$ and $\bar{r}$ are defined by Eqs. (3) and (4), and $r^*$ is the starting point of the power-law distributions, as shown in Figs. 2, 5,8 and 11.

which is the global ratio between the sex offender population and the total population, and

$$\bar{r} = \frac{1}{n} \sum_{i=1}^{n} \frac{s_i}{p_i} \tag{4}$$

which is the mean of the ratios.

Note that mathematically, self-similarity or fractal is characterized by one or many power-law relations [29]. To appreciate why power-law yields self-similar perception, let us imagine a very large number of balls flying around in the sky, with their sizes following a power-law distribution,

$$p(r) \sim r^{-\alpha}.$$

See Fig. 1. Being human, we will instinctively focus on balls whose size is comfortable for our eyes — too small balls cannot be seen, while too large balls block our vision. Now let us assume that we are most comfortable with the scale $r_0$. Of course, our eyes are not sharp enough to tell the differences between scales $r_0$ and $r_0 + dr$, $|dr| \ll r_0$. Nevertheless, we are quite capable of identifying scales such as $2r_0$, $r_0/2$, etc. Which aspect of the flying balls may determine our perception? This is essentially given by the relevant abundance of the balls of sizes $2r_0$, $r_0$, and $r_0/2$:

$$p(2r_0)/p(r_0) = p(r_0)/p(r_0/2) = 2^{-\alpha}.$$

Note that the above ratio is independent of $r_0$. Now suppose we view the balls through a microscope, which magnifies all the balls by a scale of 100. Now our eyes will be focusing on scales such as $2r_0/100$, $r_0/100$, and $r_0/200$, and our perception will be determined by the relative abundance of the balls at those scales. Because of the power-law distribution, the relative abundance will remain the same — so does our perception.

## 3. Results

Let us first focus on the State of Illinois. We computed the distributions for the total population, the sex offender population, and their ratios. The CCDFs, in log-log scale, are plotted in Fig. 2. We first note that the CCDF for the total general population and sex offenders in Illinois shown in Figs. 2(a,b) are quite different from the powerlaw population distribution of all US cities with population of 10000 or more, as reported by Newman [30]. Most interestingly, the plot for the ratio is a well-defined power-law. The starting point for this power-law behavior corresponds to $r^* = 0.0018$, which is larger than the global ratio $r_0$ but smaller than the mean ratio $\bar{r}$ listed in Table 1.

The excellent power-law relation shown in Fig. 2(c) highly suggests that sex offender clusters form a fractal process. Since power-law distribution is entirely different from a Poisson distribution, it is natural to consider zip code areas with raw risk $r_i \geq r^*$ as neighborhoods with sex offender clusters. Among the 1072 zip code areas studied, we find that 388 satisfy this condition. Therefore, about 36% of the zip code areas can be considered sex offender clusters.

It is instructive to show these sex offender clusters in a map. Since Google Earth is error-prone, we have used ArcGIS. We tried two methods. One is to represent a sex offender cluster by a circle, with its radius proportional to the raw risk $r_i$. This is shown in Fig. 3, where each circle is chosen to be red. The approach however, has a drawback: some circles can be substantially bigger than the physical size of a zip code area. To overcome this problem, we have designed a color-encoded scheme, where normal zip code areas with $r_i < r^*$ are simply represented by a white background. Each zip code area that can be considered as a sex offender cluster is represented by a single color. This yields a color map shown in Fig. 4. Since such a map preserves the actual size, sometimes one has to zoom in to see the details. One example is shown at the top right corner of Fig. 4, which corresponds to the Chicago area. We observe that when a neighborhood is small, in order to see its true "color", we have to zoom in.

Note that our results have shed some new light on two earlier studies. One is by Grubesic [27], who found that the primary sex offender cluster may morph from the entire state to a big swatch of the state of Illinois. The primary reason is that the sex offender clusters are size-invariant on a wide range of scales; therefore, when a size parameter corresponding to the population in Kulldorff's spatial scan statistic is varied, one cannot easily see which parameter best defines a sex offender cluster.

Another study is by Hughes and Burchfield [31]. They found that sensitive facilities (e.g., day care centers) are significantly more abundant in disadvantaged neighborhoods than in affluent neighborhoods. While this can partially be attributed to the least restrictive (e.g., 500 ft) residence restrictions law in Chicago, it is also due to the fact that many of those disadvantaged neighborhoods are not yet sex offender clusters.

We have carried out similar analyses on data for Ohio, New York and California. The results are shown in Figs. 5 - 13. Especially from Figs. 5, 8, and 11, we observe that sex offender clusters in those three states also form fractal processes. The key parameters for them are listed in Table 1. We find that the number of sex offender clusters in New York is the smallest.

Note from Table 1 that $r^*$ is usually larger than the global ratio $r_0$. This is to be expected, as otherwise, there will be too many sex offender clusters. However, $r^*$ may be smaller than the mean ratio, $\bar{r}$. This reflects the large scale range that the power-law distribution is defined, as is evident from Figs. 2, 5, 8, and 11. Given the large number of sex offenders registered in each state, the wide power-law scaling range may be considered a good attribute, in the sense that the sex offenders do not tightly cluster in only a few neighborhoods. On the other hand, if one wishes to have smaller number of sex offender clusters, one may use a more stringent criterion to define sex offender clusters, such as using the condition $r \geq \beta r^*$, $\beta > 1$. Clearly, the number of sex offender clusters will decrease with increasing $\beta$.

## 4. Discussions

The primary goal of the present study is to uncover the general organizing principle of sex offender clusters in the U.S. To have representative samples of sex offenders in the U.S., we have examined four states, New York, California, Illinois, and Ohio. We have found that sex offender size, where size is defined as the ratio between sex offender population and total population in a 5-digit zip code area, follows a heavy-tailed (or power-law) distribution. A heavy-tailed distribution is fundamentally different from a thin-tailed distribution such as a Poisson distribution, which forms the basis of the null hypothesis of Kulldorff's spatial scan statistic. Therefore, a power-law distribution can be used as an objective criterion for defining sex offender clusters — the start of the power-law tail defines unambiguously a threshold value, below which, a zip code area is normal, while above which, a zip code area should be classified as containing a sex offender cluster. A power-law is a defining property for self-similarity or fractal behavior [29]. The existence of power-law size distribution for sex offender clusters signifies that sex offender clusters, size-wise, self-organize into a fractal. Note that in the sex offender research community, sex offender clustering is largely attributed to the interplay of economic conditions of offenders, policies and public perceptions [17–21, 27]. While economic, policy, and social pressures are undoubtedly important elements for the formation of sex offender clusters, other processes relevant to social network formation could also be to blame.

How may the present study be utilized by policy makers, correction agencies and local law enforcement officials for developing suitable policies to mitigate sex offender clusters, ensure environmental fairness for offenders, and protect innocent women and children? These issues could be tackled by focusing on a few important variables: (1) the number of registered sex offenders in a state; (2) the number of neighborhoods without sensitive facilities such as day care centers so that sex offenders are allowed to live; and (3) total population in the neighborhoods where sex offenders can legally live. To be free of sex offender clusters, it is most desirable that sex offenders are distributed to these allowable neighborhoods as uniformly as possible. Unfortunately, this can be hardly achieved, because of many complicating factors such as housing price and availability of housing in those neighborhoods. Therefore, ideal uniform distribution for the ratio of sex offenders and total population in a neighborhood is not attainable. However, with suitable policy, it is possible to transform a power-law distribution to a distribution with a much lighter tail. Of course, a more fundamental solution is to decrease the number of sex offenders.

Our analyses have suggested many interesting future research topics in the study of crime hotspots in particular and social tomography in general. One topic is the modeling of crime hotspots, noting that the basic models for simulating hotspots are based on exponential laws [4–6], which is fundamentally different from the power-law distribution we have reported here. Another topic is to analytically or semi-analytically examine the behavior of Kulldorff's spatial scan statistic under the context of power-law distributions. The third is to zoom in the many regions in our circle- and color-encoded maps for further study. In particular, it would be tremendously interesting to examine sex offenders on scales even smaller the 5-digit zip code areas examined here, such as street-to-street level, or examine the gradients between adjacent neighborhoods. Furthermore, it would be interesting to also examine temporal correlations of sex offenses and other crimes. Such studies may shed new light on prior works on micro-scale crime variations [32–34]. Crime variations on such scales would be crucial for determining social tomography.

We also note that the notion of hotspots in crimes can be readily extended to include insurgency hotspots [35], hot-topics in science and engineering that have attracted a lot of investment attention world-wide, hot-items sales in retail stores that have caused waves of spur-of-the-moment purchasing, marine life conservation hot-zones off from the coasts by the environmental community, etc. Quantitative behaviors of these attributes can greatly enrich the notion of social tomography.

Finally, we note that the present work may be extended to enrich the study of complex networks, epidemiology, population dynamics, and ethnography. It merits noting that ethnography is closely related to culturomics [36], whose study has been greatly boosted by the recent release of googlebook's *N*gram data [37, 38].

## 5. Acknowledgments

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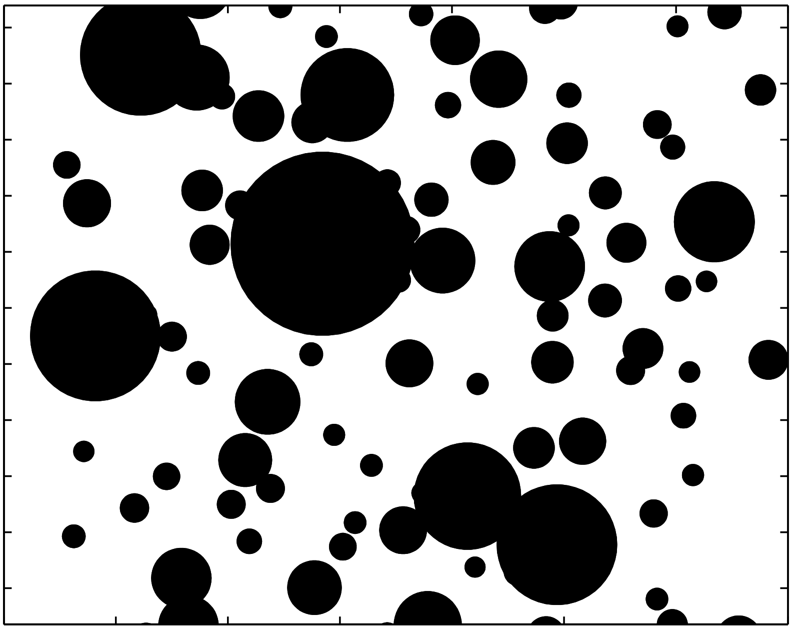

**Figure 1.** Random fractal of discs with a power-law distributed size: $P[X \geq x] = (1.8/x)^{1.8}$.

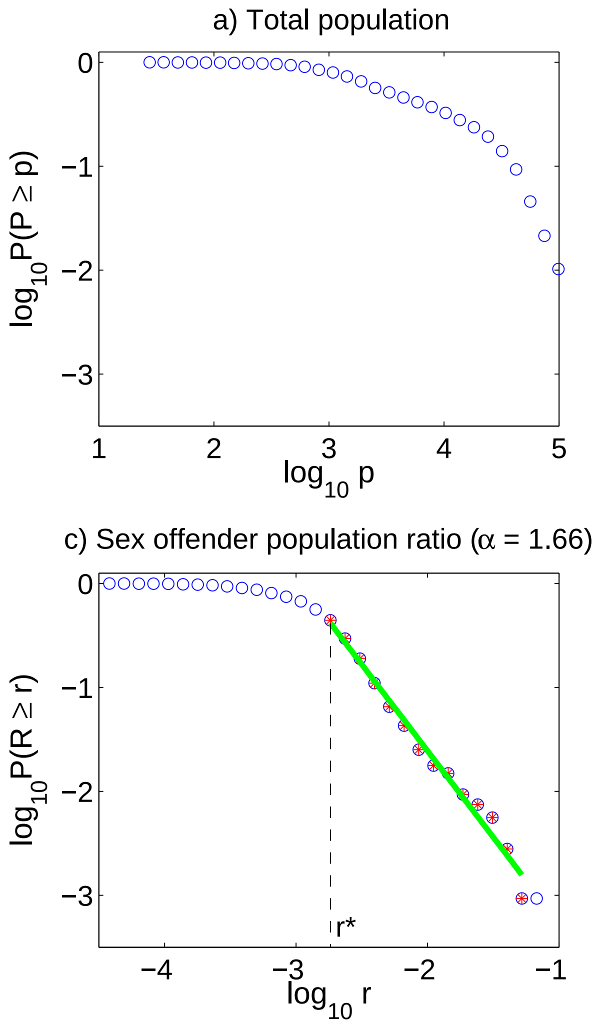


**Figure 2.** Tail probabilities $P[X \geq x]$ for total population, sex offender population and their ratio. a) total population of 1072 distinct zip codes in the State of Illinois, b) sex offender population in those zip codes, and c) the ratio between sex offender population and total population.

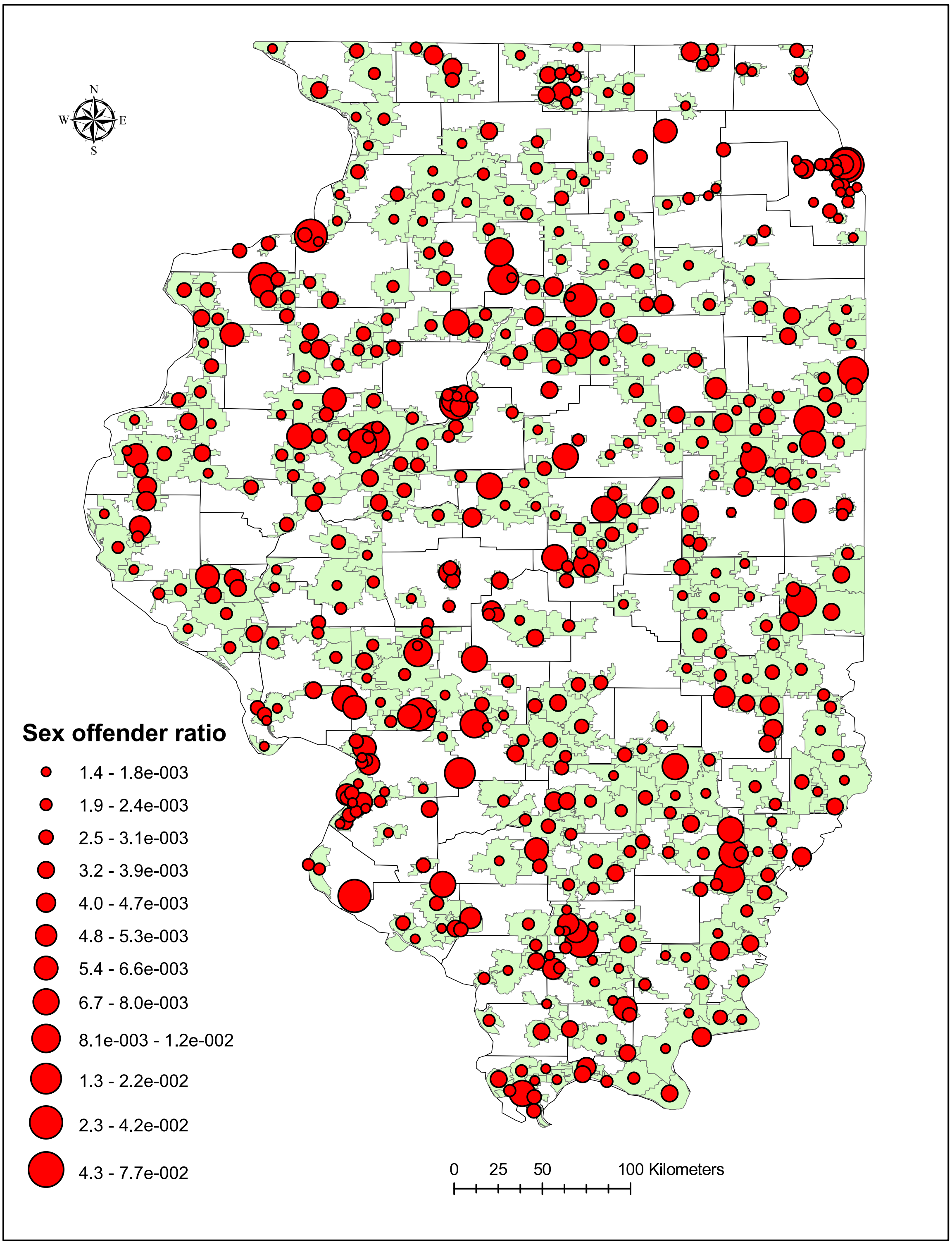


**Figure 3.** Raw risk $r_i$ for exposure to sex offenders in Illinois, 2010, as represented by red circles.

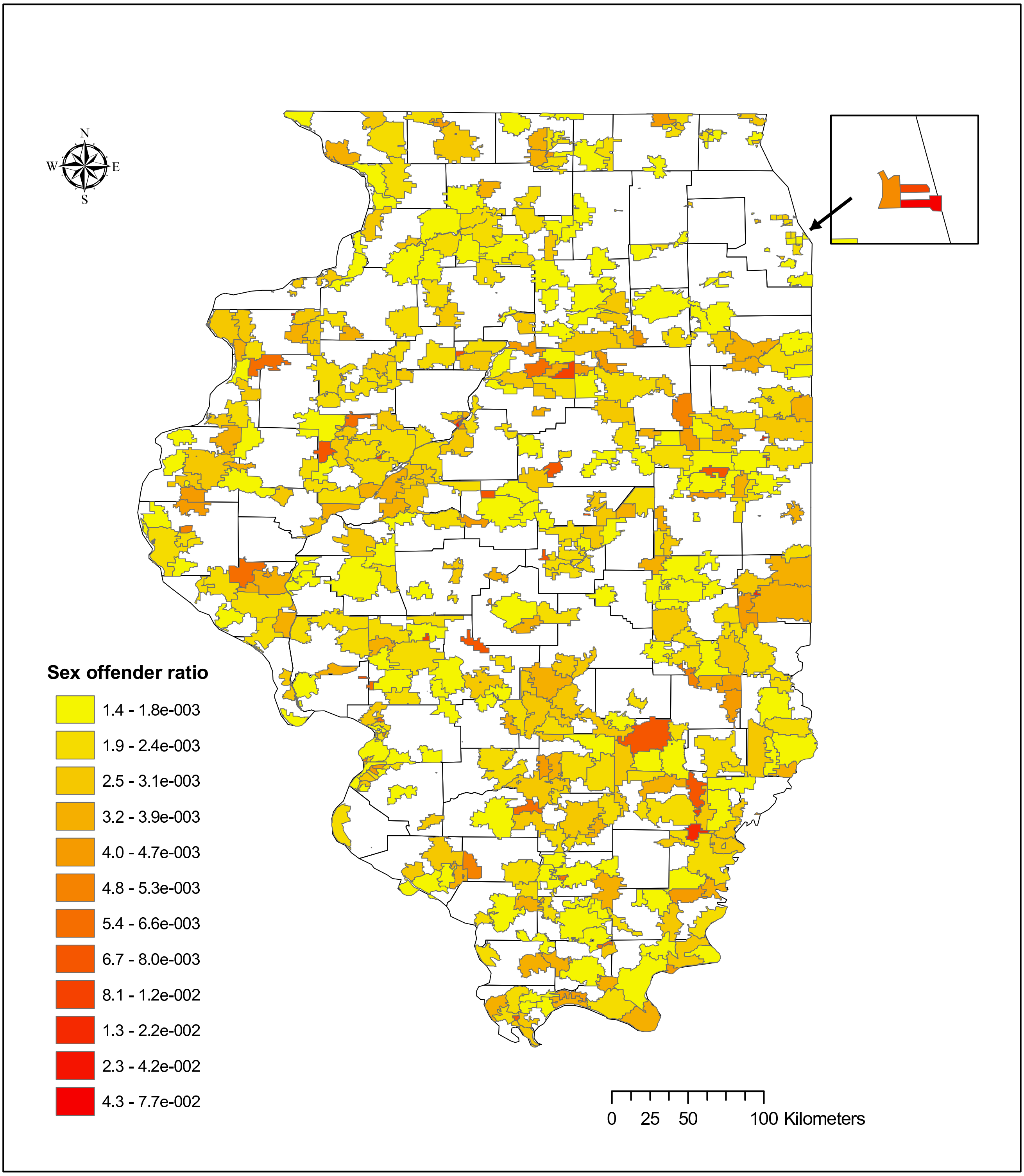


**Figure 4.** Raw risk $r_i$ for exposure to sex offenders in Illinois, 2010, as encoded by a color map.

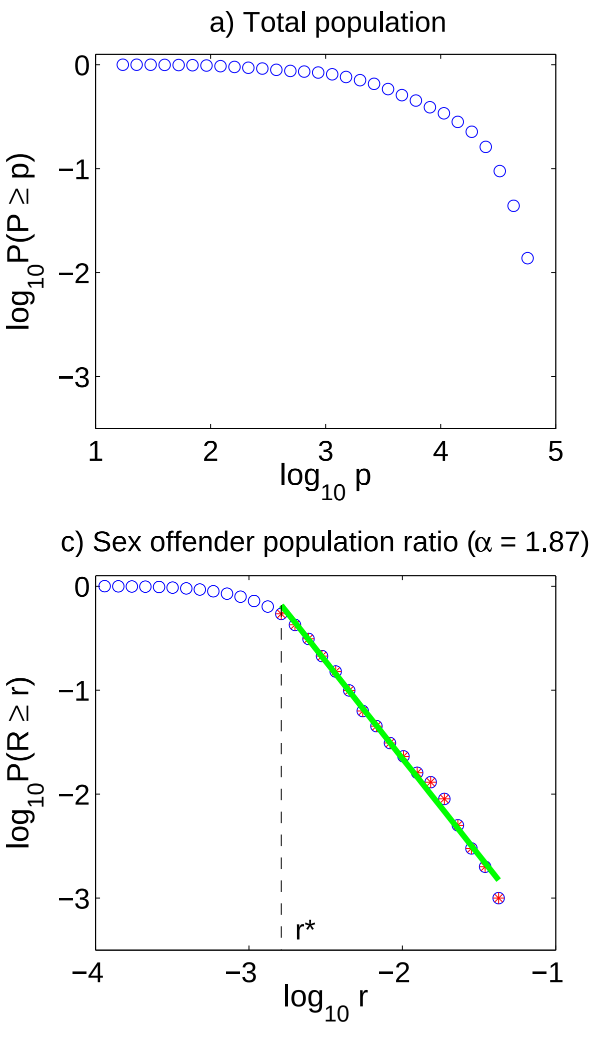


**Figure 5.** Same as Fig. 2 except for the State of Ohio.

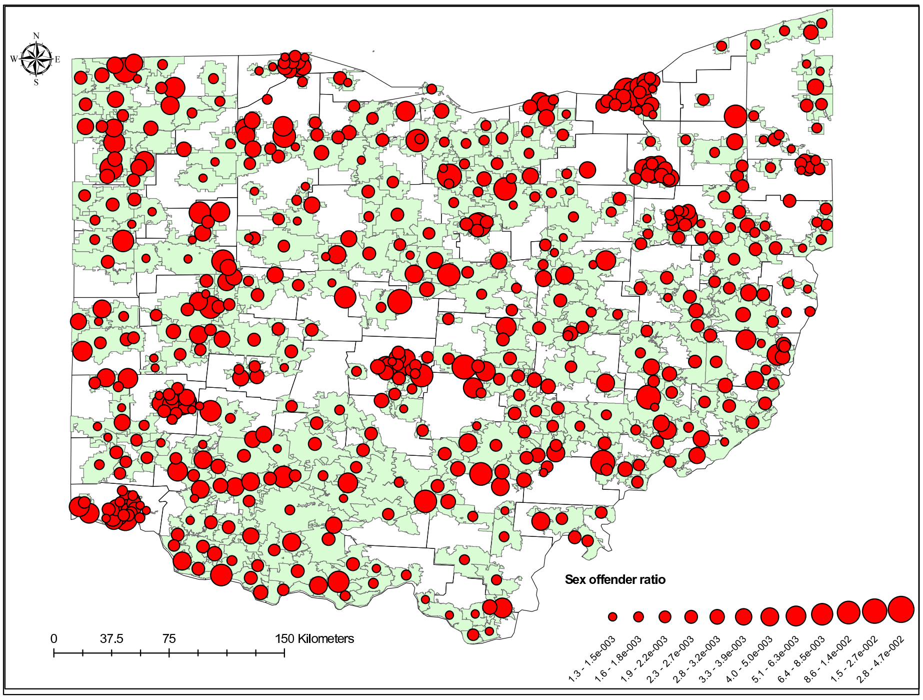


**Figure 6.** Same as Fig. 3 except for the State of Ohio.

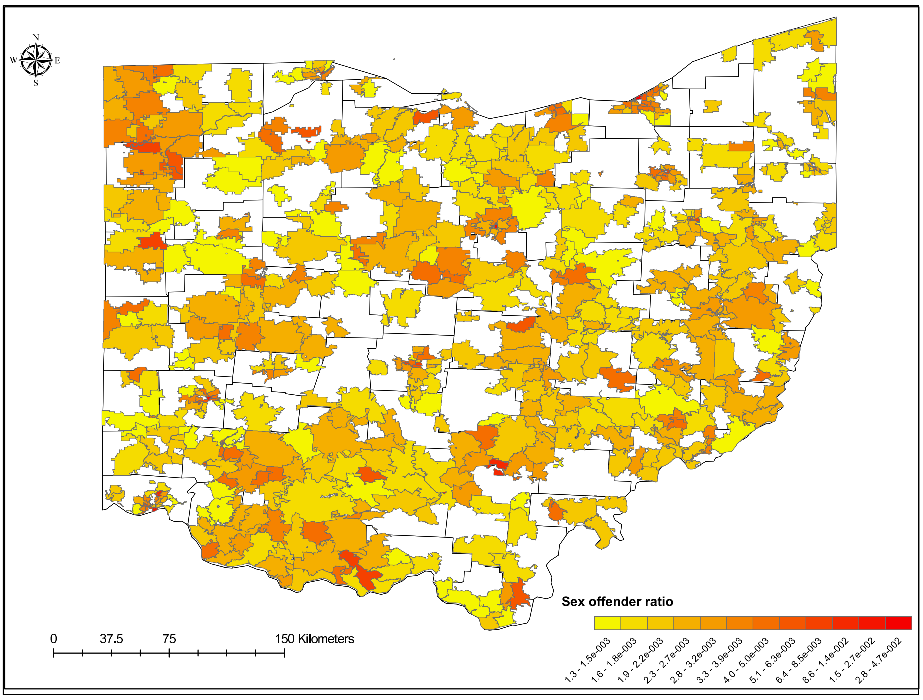


**Figure 7.** Same as Fig. 4 except for the State of Ohio.

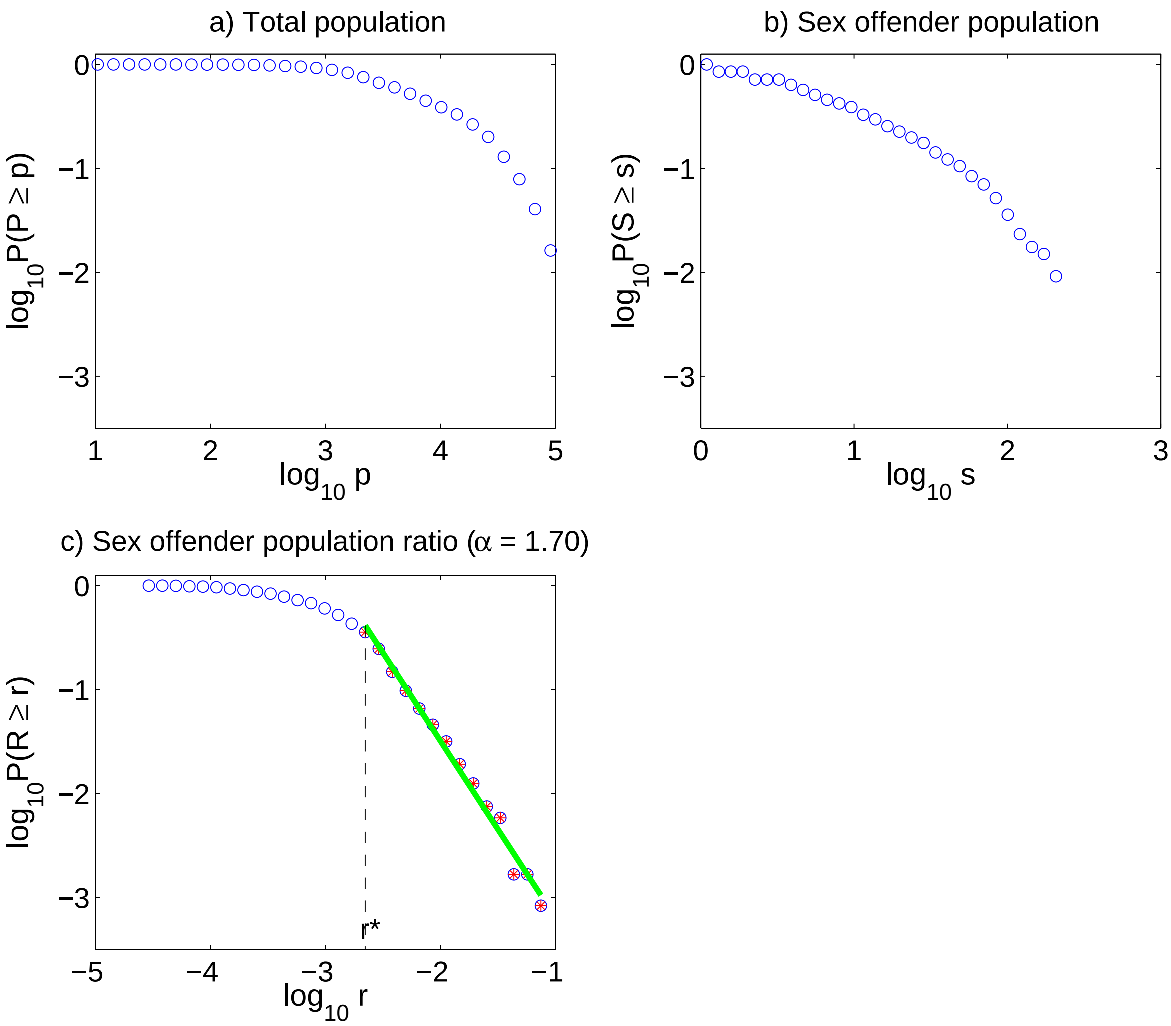


**Figure 8.** Same as Fig. 2 except for the State of New York

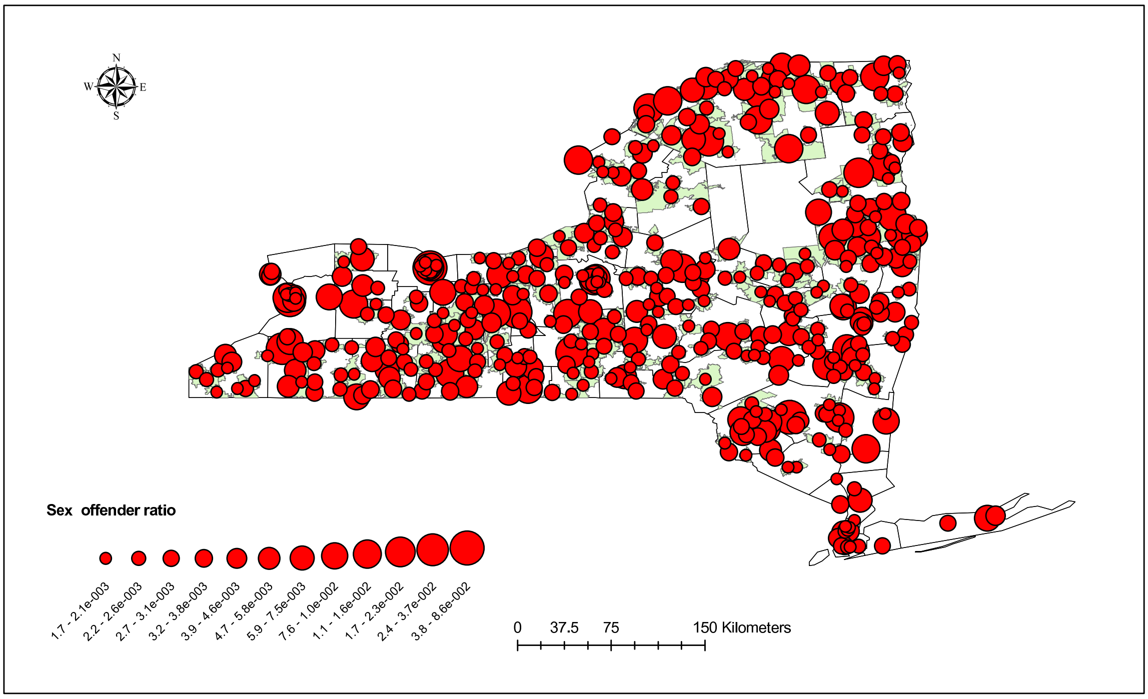


**Figure 9.** Same as Fig. 3 except for the State of New York.

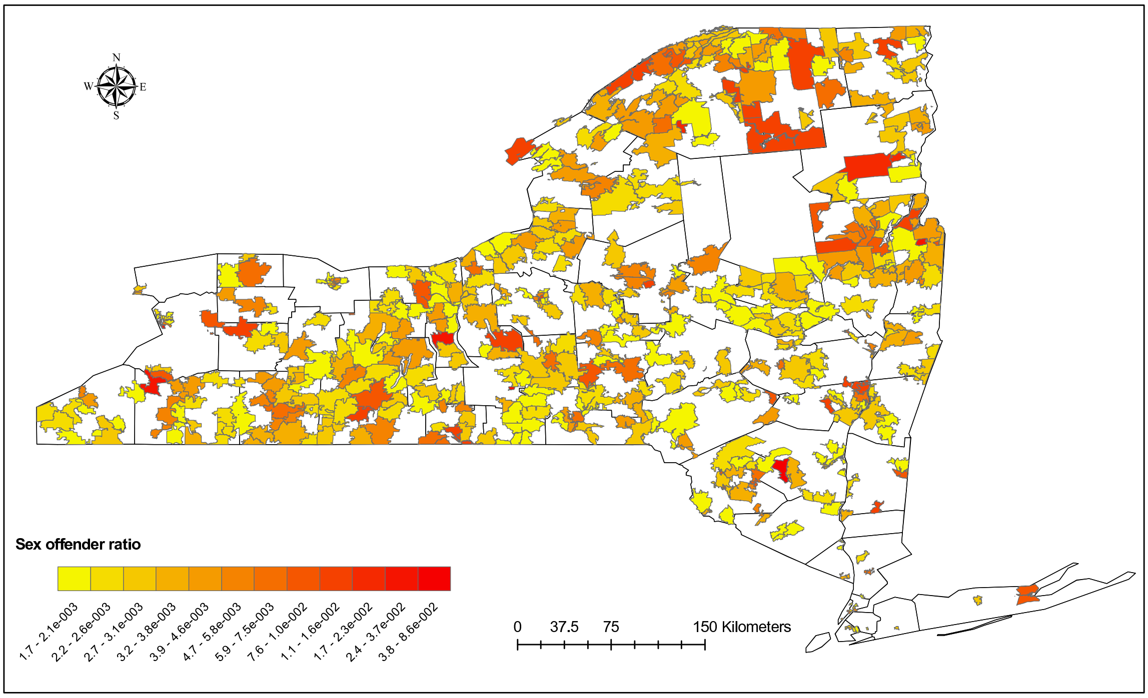


**Figure 10.** Same as Fig. 4 except for the State of New York.

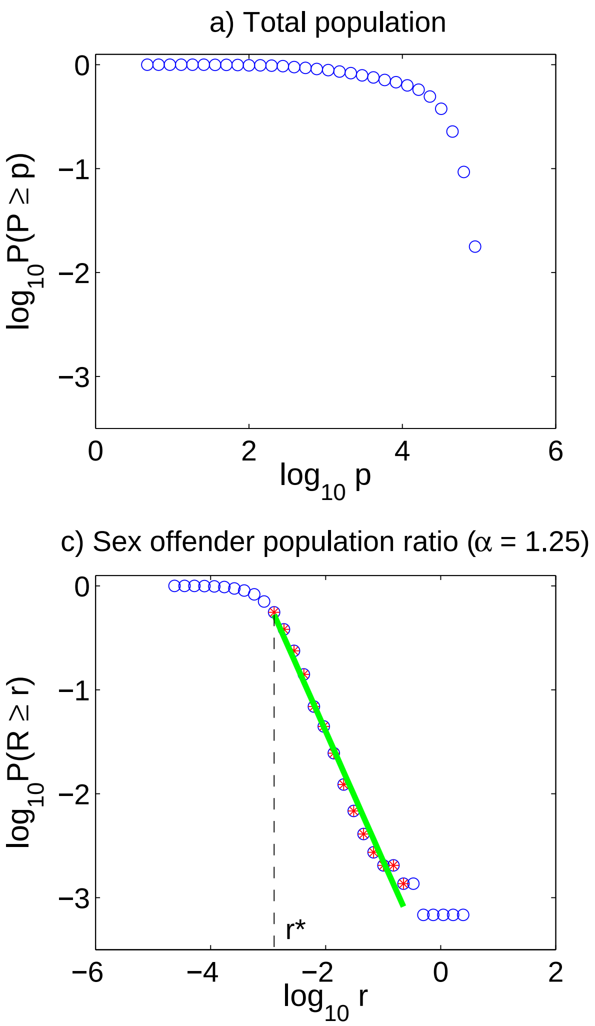


**Figure 11.** Same as Fig. 2 except for the State of California

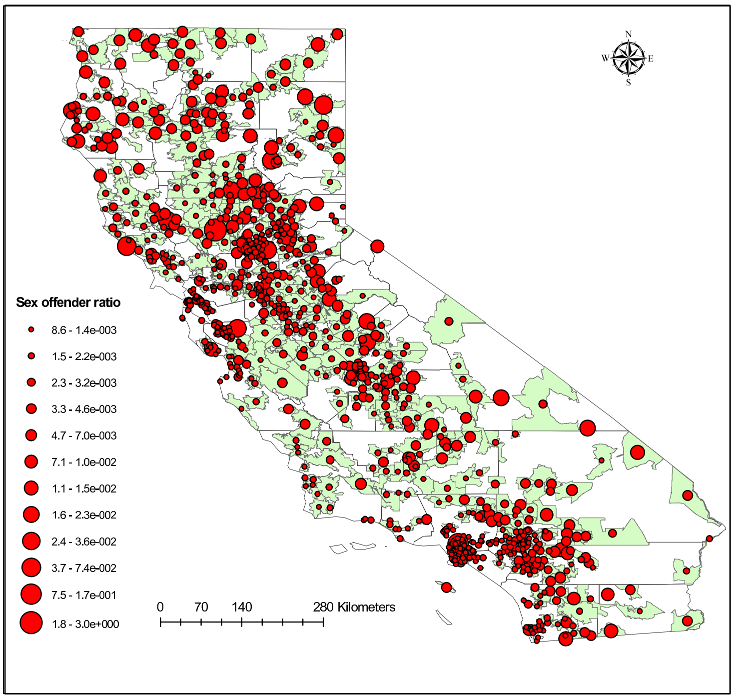


**Figure 12.** Same as Fig. 3 except for the State of California.

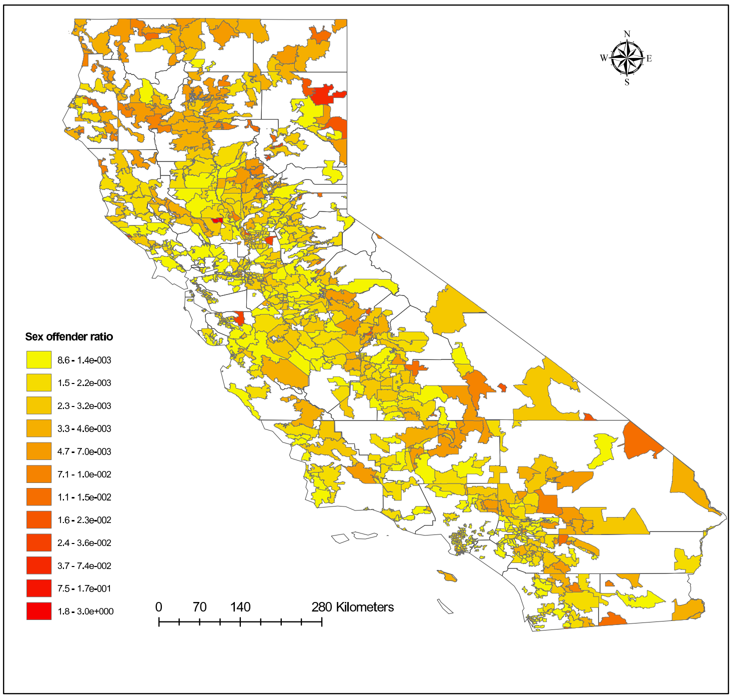


**Figure 13.** Same as Fig. 4 except for the State of California.