The effect of differential victim crime reporting on predictive policing systems

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ABSTRACT

Police departments around the world have been experimenting with forms of place-based data-driven proactive policing for over two decades. Modern incarnations of such systems are commonly known as hot spot predictive policing. These systems predict where future crime is likely to concentrate such that police can allocate patrols to these areas and deter crime before it occurs. Previous research on fairness in predictive policing has concentrated on the feedback loops which occur when models are trained on discovered crime data, but has limited implications for models trained on victim crime reporting data. We demonstrate how differential victim crime reporting rates across geographical areas can lead to outcome disparities in common crime hot spot prediction models. Our analysis is based on a simulation patterned after district-level victimization and crime reporting survey data for Bogotá, Colombia. Our results suggest that differential crime reporting rates can lead to a displacement of predicted hotspots from high crime but low reporting areas to high or medium crime and high reporting areas. This may lead to misallocations both in the form of over-policing and under-policing.

1 INTRODUCTION

Police departments around the world have been experimenting with computer-aided place-based predictive policing systems for over two decades. In a 1998 National Institute of Justice survey, 36% of police agencies employing over 100 sworn officers reported having the computing capability and data infrastructure to digitally generate crime maps [16]. Just a few years later, over 70% of agencies reported using such maps to identify crime hot spots as part of a broader adoption of CompStat approaches to policing [29]. More modern incarnations of predictive policing date back to 2008, when the Los Angeles Police Department (LAPD) began its explorations of these systems, followed shortly thereafter by efforts such as the New York Police Department's use of tools developed by firms including Azavea, KeyStats and PredPol (2012+). Far from being a US-centric phenomenon, such systems are widely used throughout Europe, the UK, and China.

More recently, predictive policing systems have come under scrutiny due to their lack of transparency [30] and concerns that they may lead to further over-policing of minority communities by virtue of being trained on biased or "dirty" data [9, 15, 26]. Critics commonly point to the possibility that such systems may produce dangerous feedback loops, vicious cycles wherein data on recent arrests is used to deploy police in still greater numbers to neighbourhoods where they zealously seek out suspicious activity and conduct even more arrests. Recent work by Lum and Isaac [15] and Ensign et al. [9] has demonstrated both empirically and theoretically how such feedback loops can arise.

Proponents and developers of predictive policing technologies have argued that such analyses are based on models of crime and policing that do not accurately reflect the types of data used as inputs to such systems, nor the types of crime that they seek to predict. The analysis of Lum and Isaac [15], for instance, convincingly demonstrates how using data on drug arrests in Oakland, CA as inputs to the self-exciting point process (SEPP) model used in PredPol would result in high concentrations of policing in racial and ethnic minority neighbourhoods. Yet PredPol has stated that they do not use data on drug-related offenses (or traffic citations) in generating their predictions, nor do they use data on arrests [23]. Azavea, the creators and former owners of the HunchLab product, likewise note that their models focus on property and violent crimes, and the crime data they use is based on victim reporting rather than arrests [7].

Secondly, proponents and developers have argued that prior studies incorrectly assume that targeted policing strategies lead to an escalation in crime detection and, correspondingly, arrests. However, the adoption of hot spot policing strategies is predicated on an anticipated *deterrence* effect. Studies of the impacts of predictive policing on property and violent crimes and on arrests at targeted locations have produced mixed results. A 2014 analysis of a randomized controlled experiment (RCT) conducted by RAND in Shreveport, Louisiana found no statistical evidence of crime reduction in the prediction-targeted locations compared to control locations[14]. Another RCT conducted in Pittsburgh reported a 34% drop in serious violent crime in "temporary hot spots" and a 24% drop in "chronic hot spots" [10]. This study found no evidence of crime displacement to nearby locations, and reported that a total of 4 arrests took place during the experiment's 20,000 hot spot patrols. A peer-reviewed study published by researchers affiliated with PredPol concluded that, while arrests were higher at predicted locations, they were lower or comparable once the counts were adjusted for differences in crime rate [6]. PredPol has reported crime drops ranging from 8-30% depending on the jurisdiction and type of crime [24].

While none of these counterarguments establish (or even claim) that the victim crime reporting data used to inform predictive policing systems is free from bias or leads to unbiased practices, they do point to a need for further investigation in settings that more closely mirror standard practice. Our work presents an initial step in this direction.

In this paper we empirically demonstrate how predictive policing systems trained exclusively on victim crime reporting data (rather than arrest data) may nevertheless suffer from significant biases due to variation in reporting rates. Our analysis is based on a simplified crime simulation patterned after district-level crime statistics for Bogotá, Colombia released by the non-profit organization Cámera de Comercio de Bogotá (CCB). We demonstrate that variation in

crime reporting rates can lead to significant mis-allocation of police. Furthermore, we discuss the limitations of using reporting rates from existing crime victimization surveys to attempt to correct for such biases.

2 BACKGROUND & RELATED WORK

2.1 Feedback loops and other biases in predictive policing

Having already described the work of Lum and Isaac [15], we focus here on [9]. Ensign et al. [9] theoretically characterize why feedback loops occur by modeling arrest-based predictive policing systems via a generalized Pólya urn model. Their analysis also considers a scenario in which both reported and detected crimes (i.e., arrests) are used to update beliefs about existing crime rates. In the latter case they show that if the reported crime rates are an accurate reflection of underlying crime, then feedback loops can be avoided if either (a) underlying crime rates across regions are uniform to begin with; or (b) detected crimes aren't considered at all. As we demonstrate in this paper, there is considerable variation in the extent to which reported crimes reflect true underlying crime levels.

Richardson et al. [26] present three case studies where there is evidence that "dirty data" may have biased the targets of predictive policing systems. Their case studies focus primarily on person-based predictive policing systems. In the case of Maricopa County, Arizona, however, the authors report on instance in which biased data may have informed a PredPol system used by the Mesa Police Department and an RTMDx system used by the Glendale Police Department. As the authors note, due to the lack of transparency surrounding what data was used and how, it is difficult to draw definitive conclusions. This, however, does not make the documented patterns of biased practices against Maricopa County's Latino residents any less concerning.

2.2 Victim crime reporting

Many countries and local governments conduct crime victimization surveys to better understand factors that drive differences in crime reporting rates, and to assess discrepancies between official crime statistics and victimization-based measures of criminal activity. According to the 2018 report released by the Bureau of Justice Statistics, which oversees the annual US National Crime Victimization Survey (NCVS), 61% of aggravated assaults, 63% of robberies, 38% of simple assaults, and only 25% rapes/sexual assaults are reported to police [20]. In this section we briefly overview different sources of disparities in victim crime reporting in the US context. We note that, while our data simulation is based on a 2014 survey conducted in Bogotá—and crime reporting rates are observed to be considerably lower there—our conclusions apply to geography-associated disparities in reporting rates in general. Our analysis indicates that, to the extent that these sources of disparity coincide with geography, we can expect significant under- or over-targeting to result.

The likelihood that a crime is reported to police has been found to be greater for older victims [3, 5, 13, 28] and when the victim is a woman [4]. It is also greater if a third party is present [4], if a weapon is present or the victim is injured [4, 32]. Furthermore, reporting rates tend to increase with the degree to which the victim is of higher socioeconomic status than the offender, which in part accounts for the greater likelihood of white victims reporting crimes perpetrated by black offenders for crimes such as assaults [31]. However, Xie and Lauritsen [31] also observe that black-on-black assaults had by far the highest reporting rate in their study (44%, compared to 25-33% for other racial pairs). This finding of high reporting rates for intra-racial black-on-black crimes was also reported in [2]. In other words, while some might expect reporting rates to be lowest in predominantly black communities, this does not appear to be borne out by the data. Furthermore, the degree of neighborhood socioeconomic disadvantage is not consistently associated with the likelihood of crime reporting [3]. An association has been observed for simple assaults, but not for robbery or aggravated assault.

There are many reasons for why particular incidents may not be reported to police. These include fear of repercussion, victim perceptions that their victimization was 'trivial', or might be perceived as such by police, or personal relationships with the offender. Furthermore, there are documented examples of police actively discouraging victims to not file complaints in order to deflate serious crime statistics [26].

2.3 Predictive policing models

Literature on predictive policing has considered a range of different modeling approaches for spatio-temporal crime forecasting and hot spot selection [11]. To the best of our knowledge, only a small subset of these models have been deployed and evaluated in practice.

PredPol, one of the largest vendors of predictive policing software in the US, has been one of few companies to publish modeling details of their hot spot prediction algorithm [17–19]. The PredPol algorithm relies on a Self-Exciting Spatio-Temporal Point Process (SEPP) model that uses the location and time of historical incidents to predict the spatio-temporal distribution of future crime within a city. Hot spot predictions for subsequent time steps can be obtained by evaluating the predicted crime distribution on a grid of cells overlaying the city. The model, which has its roots in seismology, separates crime occurrences into "background crime" and "offspring crime" with the rationale that, similar to earthquakes which often trigger close-by aftershock earthquakes, crime tends to form clusters in time and space with burglars returning to the same areas or gang conflicts leading to retaliatory violence [18].

While the SEPP method models both the space and time distribution explicitly, many other common approaches focus of one component at a time. A fairly straightforward way to predict hotspots can be achieved by time-series analysis of crime counts in predefined small spatial units such as individual segments of streets or grid cells. In a field experiment with the Pittsburgh Bureau of Police, Fitzpatrick et al. [10] used a within-cell moving average of crime counts in order to predict chronic hot spots and a within-cell multi-layer perceptron on lagged crime count features to predict temporary crime flare-ups. The authors report that the relatively simple moving average model alone was able to capture more crime on average than other models including SEPP models. The Shreveport Police Department in Louisiana conducted experiments with a logistic regression model in 2012 [14]. In addition to different

lagged crime counts, predictors also included the number of juvenile arrests in the past six month and the presence of residents on probation and parole in each of the 400-by-400-foot grid cells. Some methods focus on the spatial distribution of crime and aggregate the temporal component. Spatial kernel density estimates and risk terrain modelling, which involves risk factors beyond crime rates, are used to help identify chronic hot spots but generally require visual inspection if spatial discretization is to be avoided [11, 12].

In this study, we focus on SEPP models for crime hot spot prediction as they appear to be one of the most commonly used models based on PredPol's popularity. For comparison, we consider a moving average model as suggested by [10]. Both models are based only on the location an time of previous crimes which makes them particularly accessible to police departments.

3 METHODOLOGY

3.1 Self-Exiting Spatio-Temporal Point Processes

Self-Exciting Spatio-Temporal Point Processes (SEPP) are a commonly used class of models for applications in which the rate of events depends on nearby past events, e.g. modeling of earth quakes or the spread of infectious diseases. In the purely temporal case, this class of models is also known as Hawkes processes. We give a short introduction to SEPP, the specifications used in predictive policing and the model used in this study. A more detailed review of SEPP can be found in [25].

SEPPs separate events into two types: background events and offspring events. Background events are generally assumed to occur independently across space and time according to a Poisson point process. Each event can then cause offspring events in its vicinity according to a triggering function decaying in space and time. The rate of events at locations $(x, y) \in X \times Y \subseteq \mathbb{R}^2$ and times $t \in [0, T]$ is characterized by the conditional intensity, defined as

$$\lambda(x, y, t|\mathcal{H}_t) = \mu(x, y) + \sum_{\{k:t_k<t\}} g(t - t_k, x - x_k, y - y_k), \quad (1)$$

where $\mathcal{H}_t = \{(x_i, y_i, t_i)\}_{i=1}^n$ is the history of events up to time t which we will omit for simplification of notation. The background intensity $\mu(x, y)$ is often assumed to be time-independent while the triggering function $g(t - t_k, x - x_k, y - y_k)$ is generally chosen to be separable in time and space for computational simplicity. For each event (x_k, y_k, t_k), the number of offspring events follows a Poisson distribution with mean

$$m = \int_{X\times Y} \int_T g(t, x, y)\mathrm{d}t\mathrm{d}(x, y).$$

If properly normalized, $g(t-t_k, x-x_k, y-y_k)$ induces the probability distribution of the locations and times of these events. After model fitting, the SEPP can be used to predict the locations and times of future events. Assume we want to predict the number of events $N_{A,t}$ within an area $A \subseteq X\times Y$ at a given time $t = t'$. This prediction can be obtained by computing the integral

$$\widehat{N_{A,t'}} = \int_A \lambda(x, y, t|\mathcal{H}_{t'}, t = t')\mathrm{d}(x, y). \quad (2)$$

SEPP models have first been applied to crime data for hot spot prediction by [18]. Initially, the authors suggested non-parametric estimation of μ and g based on only background or offspring crimes respectively which requires a computationally expensive iterative stochastic declustering procedure. In subsequent work, [17] introduced a parametric approach that uses all data to estimate the background intensity with kernel density estimation and assumes a triggering function that is exponential in time and Gaussian in space. The benefit of this parametric approach is that model parameters can be be estimated with a less expensive Expectation-Maximization procedure. In field experiments with the Los Angeles Police Department and the Kent Police Department, United Kingdom, [19] forgo a complicated spatial model by fitting a cell-wise constant background intensity and a triggering function only exponential in time.

In this work, we draw on a fully parametric SEPP model that is inspired by the simulations conducted in [18]. We assume a scaled Gaussian background intensity, defined as

$$\mu(x, y) = \frac{\bar{\mu}}{2\pi(15)^2} \exp\left(-\frac{x^2}{2(15^2)}\right) \exp\left(-\frac{y^2}{2(15^2)}\right), \quad (3)$$

where the spatial deviation is chosen purposefully large to ensure support on the whole city map. Our triggering function is similar to the proposed parametric functions and takes the form

$$g(t, x, y) = \theta\omega \exp(-\omega t) \exp\left(-\frac{x^2}{2\sigma_x^2}\right) \exp\left(-\frac{y^2}{2\sigma_y^2}\right). \quad (4)$$

Choosing a fully parametric model allows us to analyze a best-case scenario of the bias introduced by differential crime reporting rates as similar models can be used for data simulation and model fitting keeping error introduced by model misspecification at a minimum. In addition, the model choice enables efficient computation of the prediction integrals in Equation 2. For crime hot spot prediction, city maps are generally split into small areas by imposing a grid with fixed cell lengths. To predict the number of crimes within a cell at time t, integration over the estimated intensity function is necessary which can be computationally expensive depending on the exact model choice. To the best of our knowledge, the model we use is similar to the model employed by PredPol's commercial hot spot prediction software.

3.2 Expectation-Maximization Procedure

The parameters of the SEPP model in Equation 1-4 are estimated using maximum likelihood. As an analytical solution is intractable, [27] introduced an Expectation-Maximization (EM) algorithm that maximizes the log-likelihood. Assuming we know the branching structure of the data set $\{(x_i, y_y, t_i\}_{i=1}^n$, i.e. which events were triggered by which previous events and which events come from the background process, we introduce a latent variable u_i which equals j if crime i was triggered by crime j and 0 if it was sampled from the background process. Given these latent quantities, the complete-data log-likelihood of the parameter vector $\Theta = (\bar{\mu}, \theta, \omega, \sigma_x, \sigma_y)$ can

be written as

$$l(\Theta) = \sum_{i=1}^{n} \mathbb{I}(u_i = 0) \log(\mu(x_i, y_i)) + \sum_{i=1}^{n} \sum_{j=1}^{n} \mathbb{I}(u_i = j) \log(g(t_i - t_j, x_i - x_j, y_i - y_j)) - \int_{X \times Y} \int_{T} \lambda(x, y, t) \mathrm{d}t \mathrm{d}(x, y),$$

where $\mathbb{I}(\cdot)$ is the indicator function. Given a data set of crime events, the EM algorithm provides an iterative procedure of estimating the triggering probabilities u_i and the parameters Θ. In the E step, we estimate the triggering probabilities based on current parameter values as

$$\mathrm{P}(u_i = j) = \begin{cases} \frac{g(t_i - t_j, x_i - x_j, y_i - y_j)}{\lambda(x_i, y_i, t_i)} & \text{if } t_j < t_i, \\ 0 & \text{else.} \end{cases}$$

and $\mathrm{P}(u_i = 0) = \mu(x_i, y_i)/\lambda(x_i, y_i, t_i)$. These latent values can then be plugged into the expected complete-data log-likelihood which gives

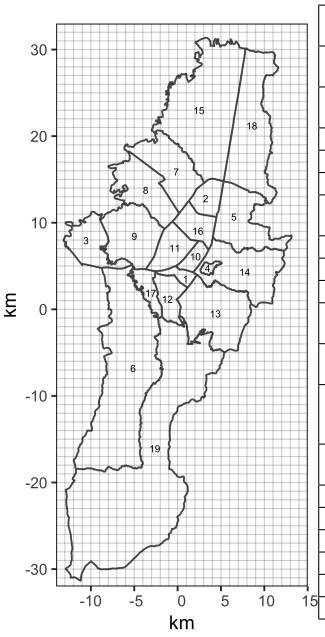
$$\mathbb{E}[l(\Theta)] = \sum_{i=1}^{n} \mathrm{P}(u_i = 0) \log(\mu(x_i, y_i)) + \sum_{i=1}^{n} \sum_{j=1}^{n} \mathrm{P}(u_i = j) \log(g(t_i - t_j, x_i - x_j, y_i - y_j)) - \int_{X \times Y} \int_{T} \lambda(x, y, t) \mathrm{d}t \mathrm{d}(x, y).$$

In the M step, we maximize the expected log-likelihood with respect to Θ and return to the E step with the new parameter estimates. This procedure is repeated until the parameter values converge.

3.3 Bogotá Victimization and Reporting Survey

Victimization rates, i.e. the fraction of the population who has been victim of a crime, and victim crime reporting rates, i.e the fraction of all crimes with victims that have been reported to the police, can generally not be assessed based on only police data but require large-scale surveys. Often, these surveys are not conduced or published with a high-enough spatial resolution to give a sense of differences at a local level. For instance, the US Bureau of Justice Statistics conducts a bi-annual National Crime Victimization Survey with around 95,000 households and publishes rates of victimization and crime reporting on a national level and aggregated by urban, suburban and rural areas [21].

In order to study the effect of differential victim crime reporting on predictive policing systems, which are generally limited to a single city, we draw on district-level data from Bogotá, Colombia collected by the private non-profit organization Cámera de Comercio de Bogotá (CCB). The bi-annual CCB crime perception and victimization survey includes approximately 10,000 randomly selected participants from all socio-economic statuses and all 19 urban districts of Bogotá. Among other questions, participants are asked to indicate whether they have been the victims of a crime in the present calendar year and, if yes, whether they have reported the crime to the police. Results of the surveys are available on the CCB website and are used to inform the definition and adjustment of the city's public policies [1]. Not all of the published reports stratify results by districts. For our experiments, we use victimization and victim crime reporting rates stratified by district based on the survey that covers the first half of 2014 [8]. Districts, population sizes and rates are depicted in Figure 1. Both the crime victimization rates and the victim crime reporting rates vary significantly between different districts with victimization rates between 5 % and 18 % and victim crime reporting rate from 13 % to 33 %.



Id	District	Pop.	Vict. rate	Rep. rate
1	Antonio Nariño	109,176	15 %	33 %
2	Barrios Unidos	243,465	12 %	22 %
3	Bosa	673,077	13 %	26 %
4	Candelaria	24,088	12 %	22 %
5	Chapinero	139,701	9 %	28 %
6	Ciudad Bolívar	707,569	8 %	17 %
7	Engativá	887,080	11 %	20 %
8	Fontibón	394,648	10 %	19 %
9	Kennedy	1,088,443	13 %	28 %
10	Los Mártires	99,119	17 %	25 %
11	Puente Aranda	258,287	14 %	32 %
12	Rafael Uribe Uribe	374,246	12 %	15 %
13	San Cristóbal	404,697	13 %	21 %
14	Santa Fe	110,048	17 %	17 %
15	Suba	1,218,513	5 %	19 %
16	Teusaquillo	153,025	14 %	19 %
17	Tunjuelito	199,430	17 %	23 %
18	Usaquén	501,999	18 %	13 %
19	Usme	457,302	9 %	33 %

Figure 1: Bogotá district map with division into 1 km×1 km grid cells for hot spot prediction. Victimization and victim crime reporting rates based on 2014 CCB survey. District differ notably in size, population numbers, and victimization and reporting rates.

3.4 Synthetic Data Generation

We simulate location and time of reported and unreported crime incidents in Bogotá districts according to the victimization and victim crime reporting rates displayed in Figure 1. In order to minimize possible errors due to model misspecification and instead concentrate on the effect of differential reporting rates, we sample data directly from a high-intensity SEPP λ and subsample according to each district's victimization rate. The background intensity of λ is a sum over bivariate Gaussian distributions centered at 14 locations spread out evenly on the Bogotá map. Each background crime triggers offspring according to a triggering function that is Gaussian in space and exponential in time coinciding with the model we are fitting (see Equation 1-4). Since the data will be used to predict hot spots on a fixed grid, we impose a grid of 1 km × 1 km cells on the Bogotá map as depicted in Figure 1. District membership of each cell is decided based on its center and each point is attributed to the district of the cell it falls into. We dicretize the time component into

daily units and simulate crime data for 2,190 timesteps (6 years) as follows:

(1) Sample a set of candidate points $C = \{(x_i, y_i, t_i)\}_{i=1}^{N}$ from λ and discard all points that fall outside of the city bounds or time horizon.
(2) For each district d and data within its bounds $C_d \subseteq C$, we subsample $n_d \sim \text{Bin}(|C_d|, p_d)$ of the points to form the true crime data set $\mathcal{D}$, where
$$p_d = \frac{\text{population}(d) \cdot \text{victimization rate}(d) \cdot 12}{|C_d|}.$$
(3) To get a data set of only reported crime, we subsample $n_d \sim Bin(|\mathcal{D}_d|, q_d)$ crimes for each district d where $\mathcal{D}_d \subseteq \mathcal{D}$ is the set of crimes falling into the given district and
$$q_d = \text{victim crime reporting rate}(d).$$

We implicitly assume that each person is victim of at most one crime which leads to the time scaling factor $2190/(365/2) = 12$ in step 2 as the CCB survey provides rates of victimization for a half-year period. In addition, district population counts are scaled by 1/40 to speed up the run time of the whole simulation. The described sampling procedure for the true data $\mathcal{D}$ ensures that crime is sampled according to population size and victimization rates but remains distributed according to a thinned SEPP that can be accessed for evaluation of the ground truth conditional intensity. Since $\mathcal{D} \sim p_d\lambda$, the true expected number of crimes in a subarea A_d of district d in time $t = t'$ can be computed as

$$\mathbb{E}[N_{A_d,t'}] = \int_{A_d} p_d \lambda(x, y, t|\mathcal{H}_{t'}, t = t')\mathrm{d}(x, y),$$

where $\mathcal{H}_{t'} = \{(x_i, y_i, t_i) \in C : t_i < t'\}$.

Figure 6 depicts a summary of the sampled number of crimes per district, the number of crimes expected according to above integral and the number of crimes as implied by the CCB survey showing that the synthetic data set has the desired rates of victimization for each of the districts.

4 RESULTS

4.1 Hot spot prediction procedure

We fit SEPP models (see Equation 1-4) on the full and reported crime data by discarding the data from the first 500 simulated time steps and training on the subsequent 1,500 days (≈ 4 years) of sampled incidents. Ignoring the first 500 time steps omits the period in which the data generating SEPP is converging to its equilibrium rate and provides a data set that more closely resembles the crime data over fixed time windows we would expect to see in practice. In addition, the time range of approximately 4 years is reasonably close to real crime data sets and falls well within the range of 2-5 years that is suggested by PredPol specifically [22].

The fitted models are used to predict crime intensities on a day-to-day basis for 189 evaluation days where, after each time step, the data for the time step is observed and added to the estimated intensity function for future predictions. On each prediction day, we compute the models' intensity integrals in each of the 1 km × 1 km Bogotá grid cells. These integrals correspond to the absolute predicted crimes per cell and are subsequently used for hot spot selection. Since police are generally only able to patrol small fractions of a city effectively, we select the top 50 cells with highest predicted crime as hot spots which corresponds to approximately 5.7 % of the city's area. Results are aggregated over 50 simulation runs where each simulation samples a new crime data set.

4.2 Equity between districts

4.2.1 Relative number of predicted hot spots. We discuss the equity of hot spot selection at a district-level and start by examining the number of predicted hot spots relative to the number of true hot spots per prediction day in each district. Assuming that police follows the models' suggestions, this measure is of practical relevance as it directly corresponds to the degree of police presence per district relative to a best-case hot spot policing program where the true crime distribution is known.

Figures 2 and 3 depict the relative hot spot counts for a subset of districts over all evaluation time steps and simulation runs. For Figure 2, we set the relative count to one for cases in which the district has zero true hot spots and the model correctly predicts zero hot spots and exclude cases with zero true but non-zero predicted hot spots. We see that the SEPP model that was trained on all crime data, i.e. reported and unreported, performs well at selecting the correct number of hot spots uniformly over all districts (S1). This observation is unsurprising given that the fitted model closely resembles the data generating model and an intact simulated data set was available for training.

In contrast, the SEPP model that was trained on only reported crime data (S2) is found to have differential performance across districts. Although in some districts, e.g. in Tunjuelito, the relative hot spot counts of the two models appear to be similar, the model with under-reporting on average overestimates the number of hot spots in districts such as Antonio Nariño, Puente Aranda or Kennedy, while underestimating the number of hot spots in districts such as Usaquén, Rafael Uribe Uribe or Engativá. The direction of the introduced error aligns with the victim crime reporting rates of the respective districts as compared to a Bogotá-wide average with fewer of the true hot spots detected in low reporting areas and instead overly many hot spots predicted in high reporting areas. In Usaquén, which with 13 % has the lowest victim crime reporting rate among all districts, only 20.4 % of the number of true hot spots are predicted on average. Meanwhile in Kennedy, which has a comparatively high reporting rate of 28 %, the model on average predicts 126.1 % the number of true hot spots.

Thus far, we have disregarded cases in which none of the true hot spots fall into a given district but the prediction model selects one or more cells. Figure 3 gives a summary of the fraction of cases with no true hot spots, further confirming the observed displacement effect of hot spot predictions. In Usaquén, the number of times crime hot spots are predicted when none of the true top 50 crime hot spots lie in the district is over twice as high in the full data SEPP compared to the reported crime SEPP. The same fraction increases more than threefold in the high-reporting district Antonio Nariño, and almost twofold in Puente Aranda. Notably, Figure 3 also shows that the displacement effect both impacts districts that almost always have areas with highly concentrated crime and districts that do not. This

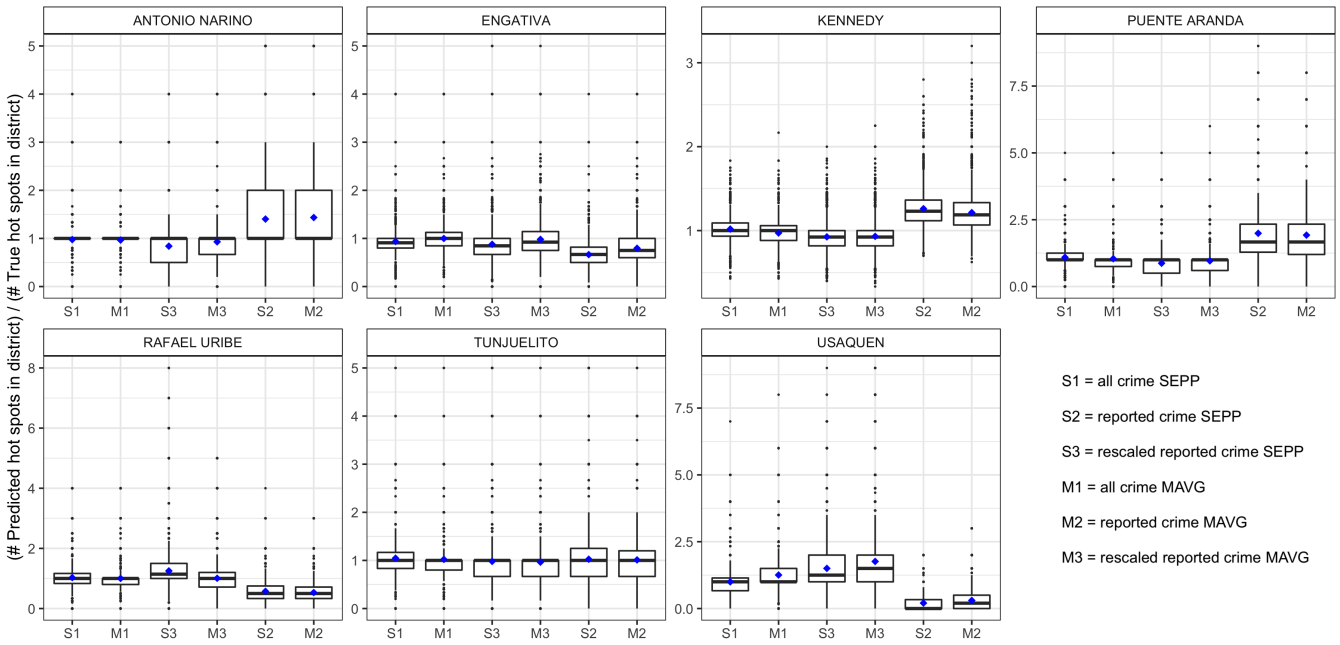


Figure 2: Relative number of predicted crime hot spots for a selection of Bogotá districts. Each data point represents a district-specific fraction at a given evaluation time step (189 days) in a given simulation run (50 runs). A total of 50 hot spots are selected at each time step. See Figure 7 for relative predicted hot spot counts for all districts.

phenomenon is a function of victimization rates, population sizes and the size of districts.

Finally, average absolute numbers of over- or underpredicted hot spots are displayed in Figure 9. Although comparison of relative counts ensures that districts of different sizes are evaluated similarly, in some cases we might be interested in the number of grid cells affected by the introduced bias as they roughly relate to the number of impacted individuals. For example, we see that the displacement of predicted hot spots based on differential victim crime reporting rates leads to on average 3.3 too many hot spots predicted in Kennedy while only 0.64 too many cells in Antonio Nariño are selected on average.

In practice, we can only train our SEPP model on reported crime incidents. However, the differential reporting rates across districts appear to lead to differentially well-measured aggregate crime levels which distorts the distribution of hot spots. If the police follows the model's recommendations, the consequence would be an unfair allocation of police patrols where areas with low victim crime reporting rates are met with artificially decreased police presence while areas with higher reporting rates are chronically over-policed.

4.2.2 Crime threshold for hot spot selection. Calculating relative counts of predicted hot spots gives insights into how much under- or over-policing we can expect per district. A natural way of comparing between districts is to look at the true crime rates required for a cell to be selected as a hot spot. If this threshold is much lower for some districts than for others, the consequence could be more average police presence in these districts despite similar or even higher crime levels in other areas.

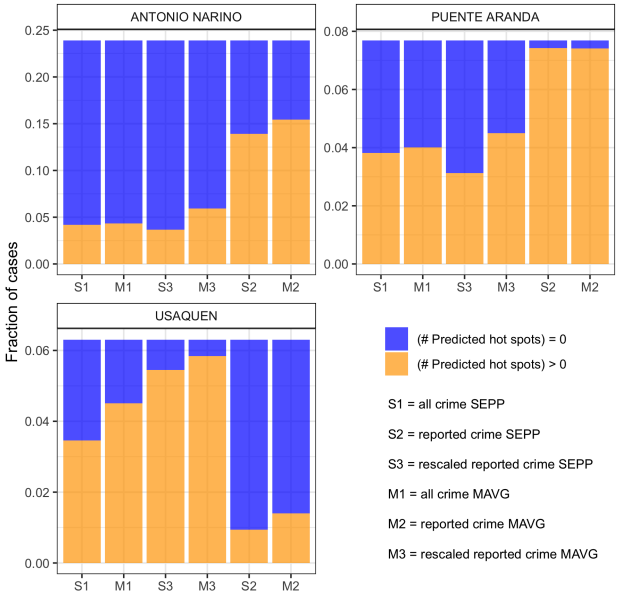
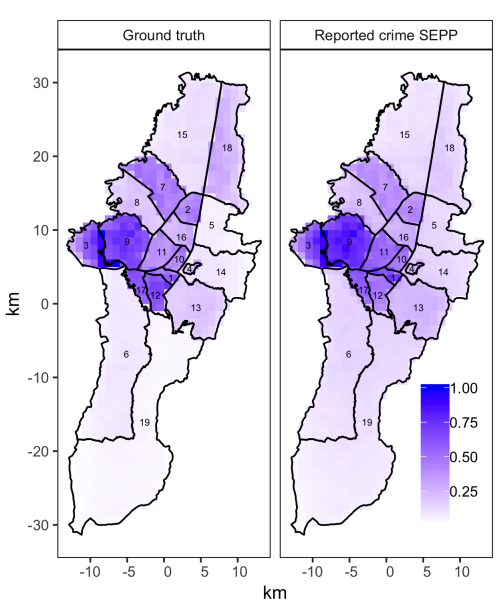


Figure 3: Fraction of prediction time steps with no true hot spots in districts. We separate instances into cases with predicted and no predicted hot spots. See Figure 8 for a version with all districts.

Figure 4 shows that the predicted crime rates implied by the reporting data SEPP model present a differentially well-adjusted approximation of true crime rates. In the Figure, we normalize the average true and predicted crime rates by dividing the rate of each cell by the Bogotá-wide maximum. This is necessary for visual comparison, since the reporting data-based intensity predictions are generally much lower than the true crime levels as a large amount of crime remains unreported in each of the districts. However, this absolute difference is only relevant from a perspective of equity between districts if accompanied by a relative change since the top 50 hot spots are selected independent of their absolute values. Comparing the normalized average crime prediction maps in the Figure, the reported crime SEPP appears to overestimate the relative concentration of crimes in the high-reporting regions Kennedy and Antonio Nariño, and underestimate the relative concentration of crimes in low-reporting districts such as Rafael Uribe Uribe and Usaquén. Moreover, crime rate prediction seems to be perform poorly in areas with little true crime. While the ground truth shows clear differences between crime intensities in areas such as Ciudad Bolívar and Usme, the model predictions in these districts appear to be almost indistinguishable.

In order to measure equity of model predictions between districts, we consider the minimum true crime rate that leads to a predicted hot spot at each prediction step and summarize the results in Figure 5. Since Bogotá-wide crime rates vary over time and this metric omits steps with no predicted hot spots falling into the respective district, the average thresholds have some variability even for full data models. However for districts that are regularly predicted to have hot spots, the full data SEPP model (S1) exhibits very similar hot spot prediction threshold of around 0.5 expected crimes per cell and time step where the low threshold is explained by the population scaling we conducted while simulating Bogotá crime data. In contrast, the model trained on only reported crime data results in varying thresholds even across districts which are regularly predicted to have hot spots. The district-wide average threshold of 0.45 true expected crimes per cell is increased in areas with low crime reporting, e.g. to a rate of 0.73 true crimes on average in Rafael Uribe Uribe and 0.62 in Usaquén. At the higher end of victim crime reporting rates, grid cells in Puente Aranda on average only require a rate of 0.32 true crimes and cells in Kennedy only 0.27 to be selected as a crime hot spots. More concretely, this means that on average the minimum true crime rate that leads to a predicted hot spot in Rafael Uribe Uribe is 2.7 times the minimum crime rate required in Kennedy. In order to rule out the possibility that Kennedy's threshold is artificially high because all of the cells in the district are regularly selected as hot spot, we examine the absolute predicted hot spot counts and find that at no time step more than 72.97 % of Kennedy is selected as hot spot area with a mean of 48.18 %.

These findings imply that crime hot spot prediction in real-world settings with differently sizes regions and differential victimization and crime reporting rates can have noticeably biased outcomes that lead to over-policing of some areas of a city while others have higher levels of crime.



Id	District
1	Antonio Nariño
2	Barrios Unidos
3	Bosa
4	Candelaria
5	Chapinero
6	Ciudad Bolívar
7	Engativá
8	Fontibón
9	Kennedy
10	Los Mártires
11	Puente Aranda
12	Rafael Uribe Uribe
13	San Cristóbal
14	Santa Fe
15	Suba
16	Teusaquillo
17	Tunjuelito
18	Usaquén
19	Usme

Figure 4: Normalized average crime predictions in each of the 1 km × 1 km grid cells used for hot spot selecetion. The left side depicts the average over true intensity integrals, while the right side uses predictions from the SEPP model trained on only reported crime data. In both cases, we normalize by dividing by the respective maximum average prediction value.

4.3 Scaling by victim crime reporting rates

A simple idea to mitigate the discussed outcome disparities is rescaling of the predicted crime rates according to the respective reporting rates. Of course, in most cases the crime reporting rates are unknown to the police. Yet if a survey like the one used in this study is available, we could imagine pairing reported crime data from a police data base with survey results in an attempt to correct the bias introduced by the crime that goes unreported. We explore this approach as an additional model in our hot spot prediction simulation by taking the integrated intensities in grid cells supplied by the reporting data SEPP and dividing them by the victim crime reporting rate of the respective district. After rescaling, we select the cells with the top 50 highest predictions as hot spots analogous to the other models.

The relative predicted hot spot counts of the rescaled model (S3) are displayed along the other models in Figure 2. Across the displayed districts, the mean relative number of predicted hot spots is just as close or closer to the number predicted by the full data model (S1) than the reporting data based predictions (S2) suggesting that the rescaling strategy was successful in reducing outcome disparities. However, this conclusion is called into question when examining the implied minimum true crime rate for hot spot selection shown in Figure 5. For example in Usaquén, the rescaled model implies a visibly lower average true crime threshold for hot spot selection than the full data model, and in Engativá the difference

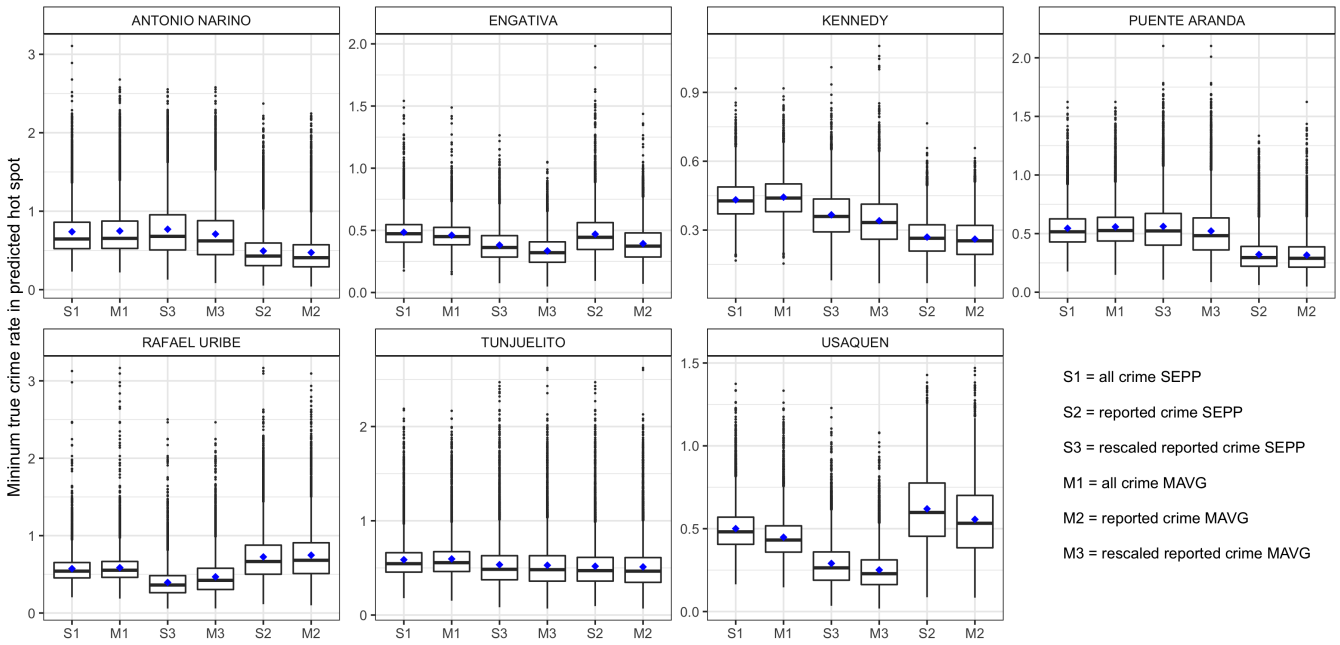


Figure 5: True crime thresholds for hot spot selection in a set of Bogotá districts. Each point corresponds to an evaluation time step (189 days) and a simulation run (50 runs). See Figure 10 for all districts.

between the full data and rescaled models appears to be larger than the difference between the full and reporting data models.

The conflict between the equity measures is observed because the relative predicted hot spot counts are an aggregate metric over all cells and not sensitive to which cells are selected in contrast to the minimum true crime threshold for hot spot selection. Rescaling of the reporting data SEPP predictions increases predictions in all cells of a district by the same factor without accounting for how much crime was unobserved in each of the cells. As a consequence, the rescaled model selects an approximately correct number of hot spots in many of the districts while the exact cells might not coincide with the true hot spots.

4.4 Comparison to moving average model

For the sake of comparison, we fit moving average (MAVG) prediction models analogous to the SEPP models on the full and reported crime data sets and experiment with rescaling the predictions obtained from the latter. MAVG models have been found to perform particularly well for detecting long-term hot spots [10] and are an easy way to predict crime in future time steps based on a sequence of crime counts in an already discretized grid representation of a city.

For our application, we aggregate crime in the same $1\,\text{km} \times 1\,\text{km}$ grid cells previously used and fit a within cell MAVG model to predict the daily crime counts on the same training data sets as before. Since a plain MAVG with finite window size poses hard tie-breaking problems and we ultimately model the time between events, we employ an exponentially weighted MAVG model. The same model parameter is estimated for the entire Bogotá grid by searching over a linear scale of bandwidths for the exponential smoothing kernel and selecting the parameter that induces minimal average error with lagged prediction on the training data set. The models are then used to predict hot spots and updated on a daily basis by adding the crime counts of the previous day.

The performances of the full data MAVG model (M1), the reporting data MAVG model (M2), and the rescaled MAVG model (M3) are depicted in Figure 2,3 and 5 alongside the analogous SEPP models. We observe that the MAVG models generally perform fairly similar to the respective SEPP model with the full MAVG model (M1) predicting crime hot spots similarly successful as the full data SEPP model. For the most part, the reporting data MAVG (M2) induces the same outcome disparities in relative hot spot counts and minimum true intensity for hot spot prediction across districts as the SEPP trained on victim crime reporting data, and the rescaled MAVG model (M3) struggles to correct the introduced bias similarly to the rescaled SEPP model.

At first glance these similarities might be surprising especially because the true data was simulated from a SEPP. However, both the SEPP and the MAVG model follow similar modeling ideas. While the MAVG model forgoes the spatial modeling by discretizing into grid cells before modeling and the SEPP method relies on discretization of the spatial predictions after the fact, both methods model the time between events with an exponential function. In addition, both models make predictions based on a weighted average of previous nearby events and the weights can be fairly similar if we assume that the spatial deviation of the triggering function is small in comparison to the size of the grid cell such that most offspring crimes fall into the same cell as their parent. This assumption is

often justified as the criminology literature tends to describe crime hot spots as micro areas of only a few blocks or street segments with high concentration of crime [11]. In fact, in their randomized controlled field trials, [19] omit the spatial component of the SEPP altogether and discretize crimes into cells before modeling.

5 DISCUSSION

This paper demonstrates how predictive policing systems exclusively trained on victim crime reporting data can lead to spatially biased outcomes due to geographically different levels of reporting. The consequence could be over-policing of certain areas of a city while others areas remain underserved by police.

Our observations are based on synthetic crime data simulated according to district-level victimization and victim crime reporting rates in Bogotá, Colombia published by the non-profit organization Cámera de Comercio de Bogotá (CCB). We employ a hot spot prediction algorithm similar to the popular PredPol prediction system and empirically evaluate equity of predictions between districts. Our findings suggest that districts with low crime reporting rates have fewer of their crime hot spots detected by the algorithm. Conversely, districts with high crime reporting rates are found to have a higher concentration of predicted hot spots than the true crime levels would justify. Moreover, the effective true level of crime required for the model to predict a hot spot is found to vary by more than a factor of two across the districts.

We further explore if known victim crime reporting rates can be used to debias hot spot predictions by scaling crime expectations appropriately. The results suggest that this is only partly successful when reporting rates are known at a district level but hot spots are predicted at a smaller individual cell level since noise introduced by individually thinned crimes is propagated to the rescaled predictions which makes singling out of specific cells in comparison to other cells in the same district difficult.

Our work presents an initial step in the direction of understanding the effect of bias in victim crime reporting data on predictive policing systems. This is relevant as there is evidence that reporting data is used to inform predictive policing models in practice [7] and previous work has predominately focused on feedback loops and the potential harms of arrest data based predictive policing systems [9, 15].

5.1 Limitations

5.1.1 Crime location vs. survey location. Victimization surveys generally provide us with information on crime reporting based on where people live, not based on where crimes occur. On a small scale like a single city, this spatial disparity makes it hard to take survey-based information into account for police allocation. Since this study is based on fully simulated data relying on exclusively survey information, this complication is of limited relevance to our empirical findings and we purposefully omit a Bogotá-specific interpretation of the observed disparities for this reason.

5.1.2 Static reporting rates and potential deterrence effects. Thus far, we do not take the effects of the actual interventions in the form of patrolled hot spots into account. We hypothesize that both victimization rates and victim crime reporting rates can be susceptible to police presence and a model that jointly describes the interplay of crime, reporting rates and police deployment is required for a more complete picture. One component currently omitted is a deterrence effect of policing. Failing to consider such effects could result in the reallocation of police patrols away from neighbourhoods where they are having the intended deterrence effect, precisely because reported crime rates would be lower when police are successful in deterring crime.

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A SUPPLEMENTARY FIGURES

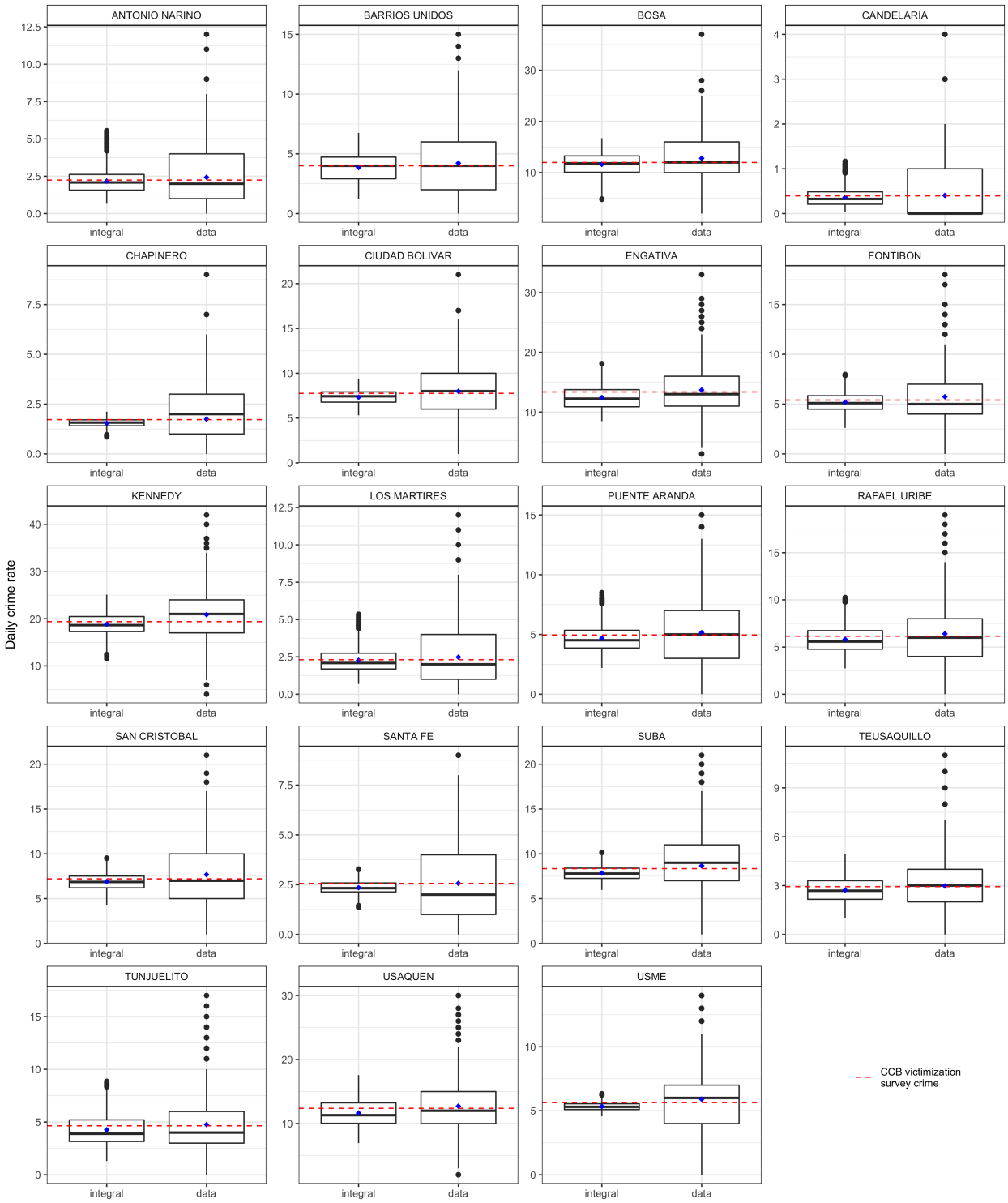

Figure 6: District-wise sanity check of synthetic crime data over all 2,190 time steps. The average daily counts of simulated data align well with the rates obtained by integration of the data generating thinned SEPP and the desired rates implied by the CCB victimization survey.

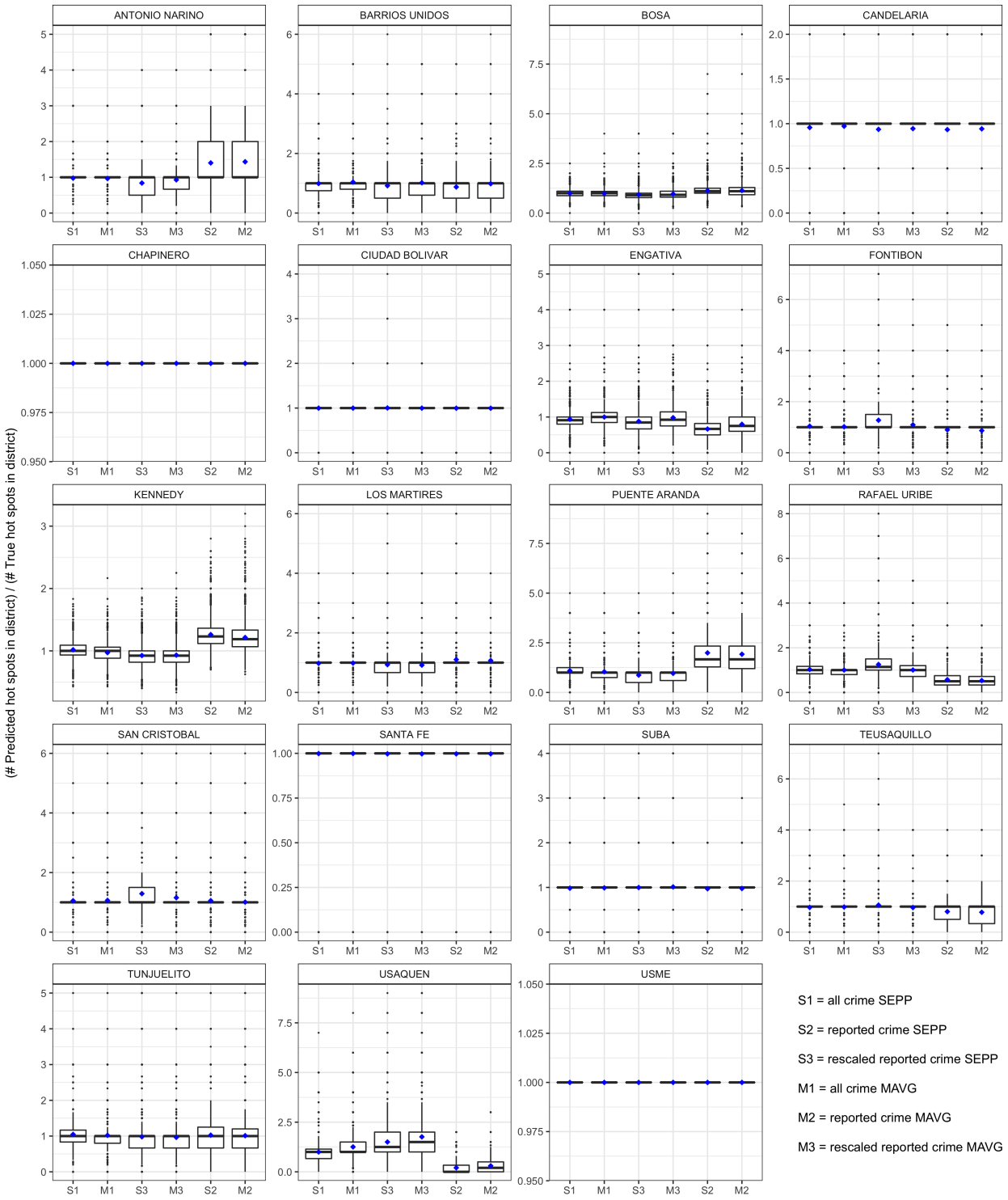

Figure 7: Relative number of predicted crime hot spots in Bogotá districts. Each data point represents a district-specific fraction at a given evaluation time step (189 days) in a given simulation run (50 runs). A total of 50 hot spots are selected at each time step. If both the true and predicted number of hot spots is zero, we set the relative count to one. Cases for which the number of predicted hot spots is non-zero but no true hot spots are available are excluded for visualization.

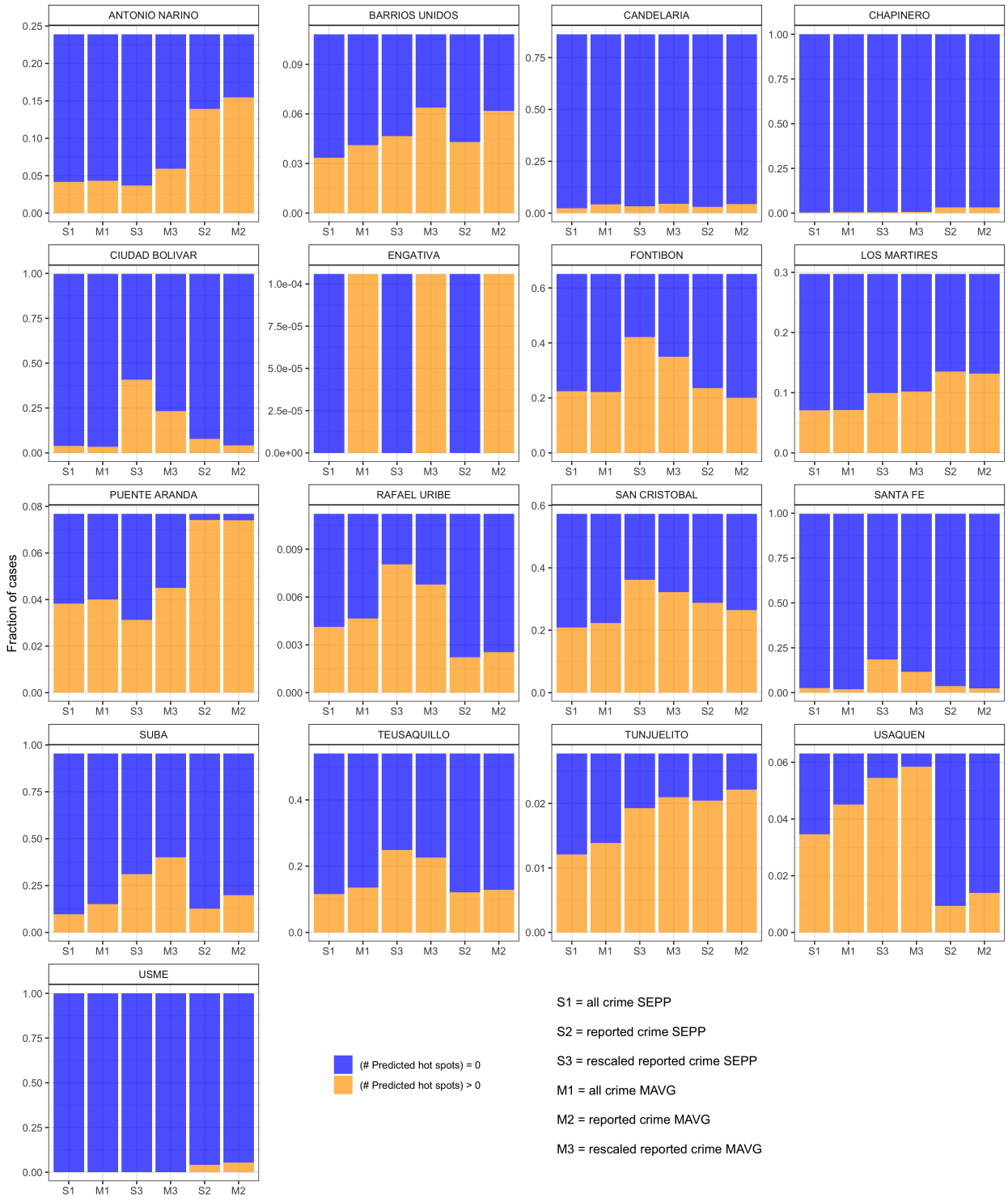

Figure 8: Fraction of prediction time steps with no true hot spots in district separated into instances with predicted and no predicted hot spots. Ratios are computed over all evaluation time steps (189 days) and all simulation runs (50 runs) with 50 hot spots selected at each step.

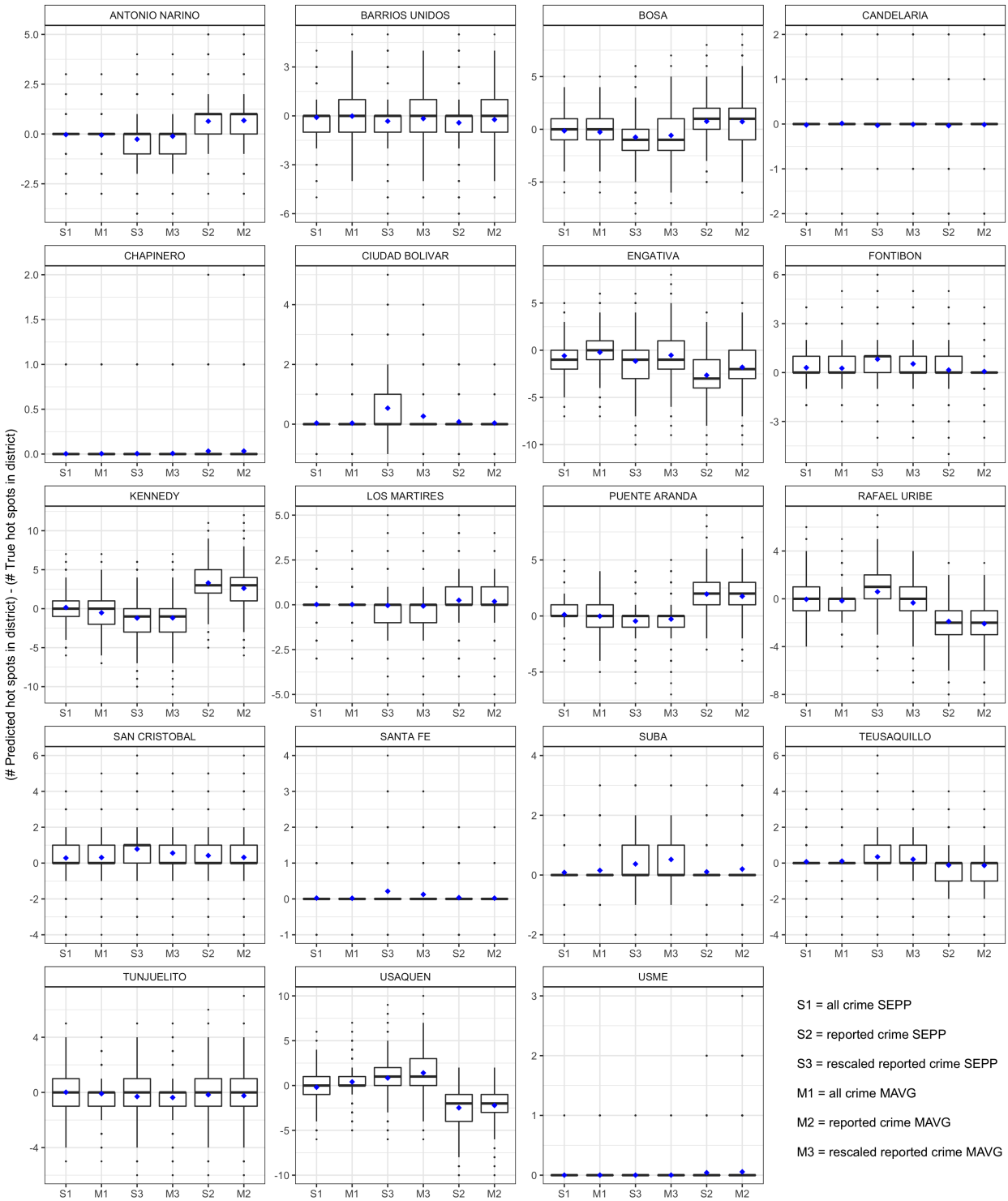

Figure 9: Absolute number of overpredicted hot spots over all evaluation time steps (189 days) and all simulation runs (50 runs) with 50 hot spots selected at each step.

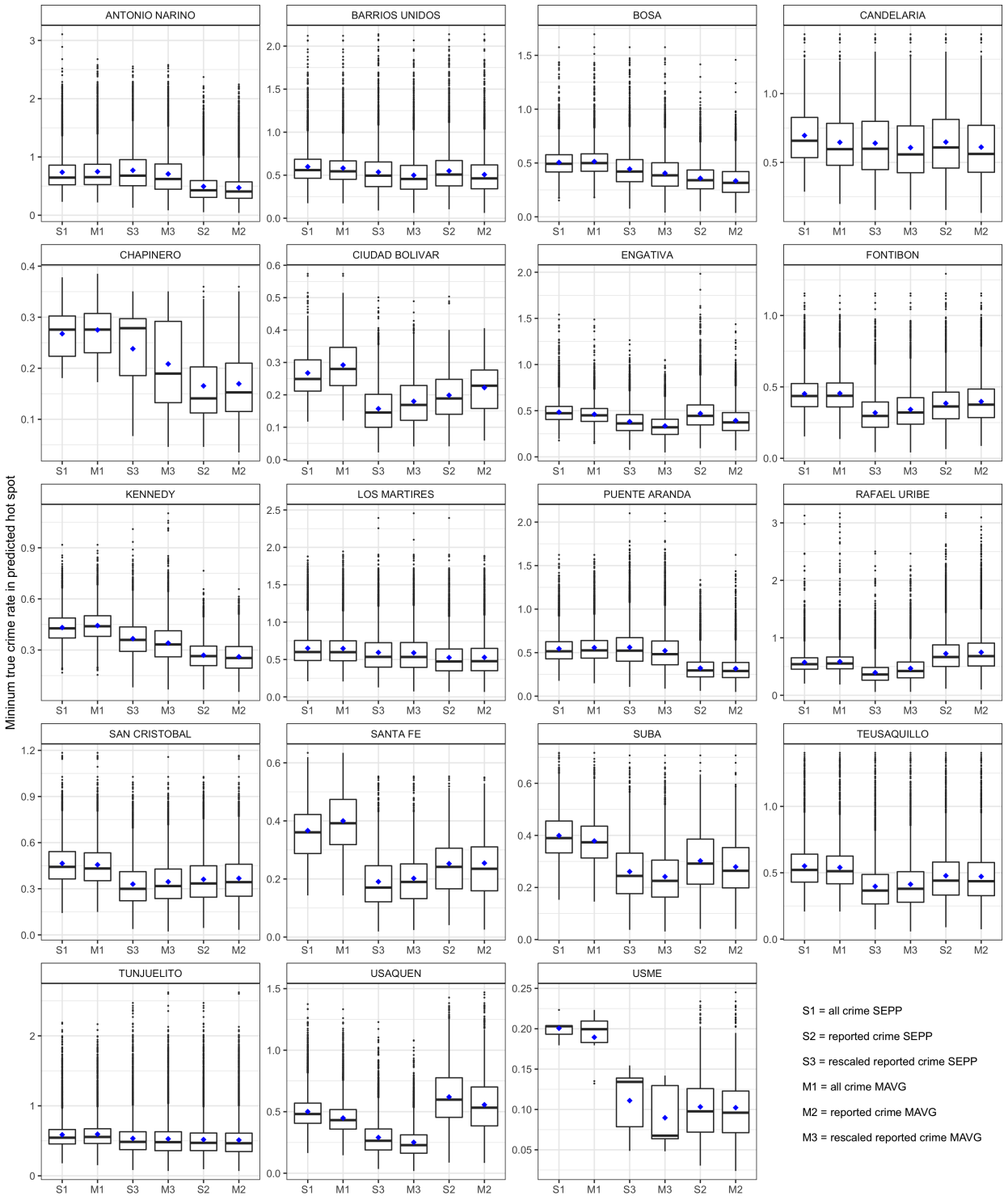

Figure 10: True crime thresholds for hot spot selection in Bogotá districts. Each point corresponds to an evaluation time step (189 days) and a simulation run (50 runs). A total of 50 hot spots is selected at each step, and cases in which no hot spot is predicted within the district are omitted for visualization.