Article

Measurement of Potential Over- and Under-policing in Communities

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Abstract Over- and under-policing of neighbourhoods can undermine public trust and confidence in the police as well as the broader justice process. This study reports on attempts to operationalize and test a spatial indicator of potential over- and under-policing, where over-policing is defined as a level of police presence at a particular location that is greater-than-expected, given the level of public demand for police services, current police enforcement strategy, and community preference regarding police activity. Automated Vehicle Locator data and Computer-aided dispatch logs from the Seattle Police Department, as well as data drawn from community-based surveys, are modelled using a Geographic Information System. The model uses 2-week data windows to provide timely and actionable information that can be rendered for decision makers in a CompStat style accountability and management forum. Such an approach has potential utility for police management, as well as for community engagement and reform efforts aimed at addressing the problem of over-policing.

Introduction

Individual police behaviour is often the subject of intense scrutiny in the wake of high-profile killings of Black, Indigenous, and People of Colour community members. However, police management and the systems by which police leadership exercises control are critical to these outcomes. Disparate over- and under-policing of communities can undermine public trust and confidence across the criminal justice system (Perry, 2006; Hough, 2012; Goldsmith and Harris, 2012;). Traditional approaches to patrol resource management rely on the autonomy and discretion of the officer. Much in the way that machine learning can inherit bias from a training dataset, particularly in the criminal justice system (Yapo and Weiss, 2018), human experiences colour perceptions of reality, and discretionary behaviours are especially subject to this influence. Although some have expressed concern about the extent to which these

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limitations can be mitigated (Lum, 2017), awareness of bias or biasing effects are thought to be effective. A more directive approach to patrol deployment and problem solving can mitigate some of these effects. In addition, the analysis of data depicting where police spend their discretionary time is an asset for police managers.

Understanding police patrol behaviours is an important first step to contextualizing community concerns around over- and under-policing. The amount and/or type of police services being provided at a particular location is largely a function of the public demand for police services (e.g. calls for service originating from the 911 system), as well as existing police enforcement strategies for that location (e.g. directed patrol activity and problem-oriented policing). There is also a degree of community preference for police enforcement activity as well as baseline crime levels and tolerance for deviance that may manifest in actual police behaviour, or the 'vigour' of response (Klinger, 1997). These concepts (demand, strategy, and preference) help us to define the expected level of police presence at a particular location, with which one might judge whether an appropriate amount of policing is occurring. Absent the deliberate action of officers (such as organized reductions in service due to labour disputes or other causes) or actual lack of police capacity (which refers to reduction in police services as a result of lack of resources), what remains might then be termed 'under-policing': A lower-than-expected level of police presence at a particular location, given the level of public demand for police services, current police enforcement strategy for the location, and community preference regarding police activity at that location. 'Over-policing' is then the opposite condition: A greater-than-expected level of police presence at a particular location, given the level of public demand for police services, current police enforcement strategy for the location, and community preference regarding police activity at that location.

Over-policing is a frequently heard complaint within some neighbourhoods and it is generally thought to have the greatest potential to undermine public trust and confidence in the police. However, there is limited research that directly examines the relationship between over- or under-policing and other criminological constructs such as hot spots policing and police legitimacy. This lack of research is concerning because of the potentially disproportionate impact on marginalized populations (such as those experiencing homelessness, and persons with mental illness) and disadvantaged communities. For example, to examine over- and under-policing, Boehme *et al.* (2020) operationalized over-policing based on respondent perceptions of excessive use of force in their neighbourhood and under-policing as a scale composed of multiple question responses (e.g. 'How much of a problem is the police not patrolling area or responding to calls from area?', 'Police in neighborhood are responsive to local issues'). These researchers found that persons of colour, to varying degrees, were more likely than white persons to perceive both over- and under-policing as an issue in their neighbourhood. This is consistent with research that has examined the impact of over-policing in indigenous communities (Perry, 2006; O'Brien, 2021) and among other minority communities (Ben-Porat and Yuval, 2012). To be sure, perceptions of over- and under-policing are complicated and the effects of additional police presence on crime are complex and may differ across racial groups with disproportionate burdens, but also disproportionate benefits (Chalfin *et al.*, 2020).

Measuring the dosage of policing in hot spots has long been a subject of interest (Koper, 1995), and our field is beginning to develop methods for estimating treatment fidelity and dosage in micro-locations, as well as making managerial decisions about resource allocation, using Global Positioning System (GPS) tracking devices including radios and Automated Vehicle Locator (AVL) data (Weisburd, 2013, 2016, 2021; Telep *et al.*, 2014; Wain and Ariel, 2014; Kochel *et al.*, 2015; Weisburd *et al.*, 2015; Gibson *et al.*, 2017; Mitchell, 2017; Blanes i Vidal and Matrobuoni, 2018; DeAngelo *et al.*, 2020). In particular, DeAngelo *et al.* (2020) and Weisburd (2013, 2016, 2021) have demonstrated the utility of AVL data as a general indicator of police presence for exploring response time, car accidents and injury, and crime preventative effects of police patrol. For example, Weisburd (2021) aggregated AVL data to the hourly level within beats in Dallas, TX, and used a novel instrumental variable (assignment of patrol vehicles to calls outside their assigned beats) to study the effect of police presence on crime, finding that a 10% decrease in police presence resulted in a 7% increase in crime.

Following this groundbreaking body of work, we offer a somewhat similar approach for identifying potential over-policing that puts police departments and the communities served in a better position to address strained police–community relations. While these earlier efforts are focused primarily on the effect of police presence on crime, our focus is on how police presence might affect community perceptions of police. Thus, the presence of a police vehicle may contribute a deterrent effect on crime, but at what potential cost to community perceptions about police presence? Can police actively monitor police presence and identify areas where that presence may be excessive?

In December of 2011, the Civil Rights Division of the US Department of Justice, in conjunction with the US Attorney's Office for the Western District of Washington, published the findings of a pattern or practice investigation of the Seattle Police Department (SPD) stemming from allegations of unconstitutional policing (US Department of Justice, 2011). The resulting Consent Decree led to the creation of the Performance Analytics & Research (PA&R) section in order to meet the research and analysis needs of the department in demonstrating compliance. The PA&R serves as a research and development arm of the SPD, and sponsors projects like the present effort in order to advance science while closing the distance between scientific discovery and practice.

This article reports on our attempts to develop and test a method for identifying potential over- and under-policing of neighbourhoods in Seattle, WA, through the analysis of AVL data, Computer-aided dispatch (CAD) log data, and attitudinal data drawn from the Seattle Public Safety Survey. In the next section, we outline the data, methods, and results of an initial development effort, highlighting some of the potential pitfalls one may encounter when working with these data, and some of the potential shortcomings of the method. We then discuss the utility of the data for accountability and management purposes and conclude with thoughts about future directions for research in this area.

Data and methods

In 2015, the Center for Open Policing sued the SPD for access to AVL data under the Washington State Public Records Act, RCW Chapt. 42.56, and won. In addition to 'approximately $30,000 in penalties, costs and fees', the SPD was forced to produce a redacted version of these data (Hyde and Ferguson, 2015), beginning a long effort to better understand operational vulnerabilities and practical uses for AVL data. After 'safing' the data[1] and delivering it to the plaintiffs, the present research team was engaged to explore other vulnerabilities and uses. The method described and tested in this article is typical of the culture of collaborative innovation established by PA&R.

Variables

In order to operationalize *police presence*, we relied on a literal indicator, AVL data, which consists of

[1] GPS tracks leading to or clustering around residences of officers with 'take home' vehicles and other sensitive locations (safe houses, critical infrastructure), were randomly redacted to eliminate the track to and visual cluster around these locations but so as not to leave a distinctive void.

time-stamped GPS 'pings' returned from police vehicles (every 6 s while the vehicle is in normal operation, and every second while the vehicle is in emergency operation). These data identify the location of police vehicles in time and space, and include time stamps, a unit identifier, and X–Y coordinates.[2] There are limitations to AVL data (officers may not always be with their vehicle, some areas will have bike and other specialized patrols, and some pings may be influenced by geography and the strength/quality of the GPS signal); however, for purposes of this analysis, AVL data are considered a reasonably proximal indicator of police presence. Working with AVL is a challenging 'Big Data' problem; for example, during a 2-week period in the City of Seattle the resulting AVL data file would consist of around 3 million records. Because of the complexity of working with this type of data, we restricted our initial efforts to a single precinct (the East precinct, which is one of five precincts and contains mixed-use commercial and high-density housing districts as well as single-housing residential areas) and a 2-week period during the month of August, 2013.[3] A 2-week period was chosen as a representative sample of police activity in the precinct across different officers and shifts. Additionally, most CompStat forums are conducted semi-monthly with a 14- and 28-day review period, which aligns this effort with a realistic use case. This resulted in a total of 372,804 records.

We operationalized the public demand for police presence as all 911 and non-911 telephone calls requesting police services, as well as alarm calls. Demand for police services is a complex construct (Laufs *et al.*, 2021) and calls for service data have well-known limitations (Klinger and Bridges, 1997) but we rely on them here as they are the only source of which we are aware for information about public calls to the police and other logged police activity that are available in a semi-detailed and contemporaneous fashion. The CAD log data include time stamps, fields describing the nature and priority of call, address, and X–Y coordinates. After removing records with no dispatch or primary unit identified, there were 3,186 CAD logs for analysis during the selected 2-week period. Sixty-three percent of the logs were classified as 911 calls ($n = 1{,}198$, or 38%), non-911 calls ($n = 713$, or 22%), and alarm calls ($n = 95$, or 3%).

The other 37% of CAD logs were classified as on-view activity, and relatively higher frequencies included preventative patrol ($n = 244$, or 8%), premise checks ($n = 236$, or 7%), suspicious persons ($n = 197$, or 6%), and traffic stops ($n = 128$, or 4%). We use these data to operationalize enforcement strategy.

We operationalized community preference using Seattle Public Safety Survey data drawn from an annual survey that is part of an ongoing initiative to establish tailored community policing plans in Seattle neighbourhoods, called the Micro-Community Policing Plans (MCPP).[4] The SPD MCPP is a collaboration between the SPD and Seattle University's Crime & Justice Research Center implemented in 2014 through a Community-Oriented Policing Services collaborative practitioner–academic grant. The initiative was implemented at a grass-roots level calling for precinct captains to work with community members to develop 'micro-community policing plans' for each of Seattle's 59 micro-communities (neighbourhoods). The MCPP consist of priorities and strategies developed through engagement between

[2] Different CAD/RMS systems geocode in different formats. Geocoding in use for the City of Seattle is a Projected Coordinate System, which is not limited by the error introduced by spherical projections.

[3] We recognize that these data are somewhat dated, however, as previously noted AVL data are generally regarded as sensitive and can be difficult to obtain. These data were available for the present study because they had already been produced as part of an unrelated public disclosure request. The 2-week period in August was selected because demand for police service in Seattle CAD event data tends to peak between June and September, with lows during and around the month of February.

[4] See: https://www.seattle.gov/police/information-and-data/mcpp-about.

the police and the community and through data collected through the Seattle Public Safety Survey. The Seattle Public Safety Survey instrument was developed as part of the SPD MCPP pilot, has been administered annually, and is now in its seventh year. The MCPP collaboration led by a research team comprised two faculty members and student research analysts who work in paid civilian positions assigned to one of the five Seattle Police Precincts tasked with assisting precinct captains and personnel with MCPP-related tasks and Seattle Public Safety Survey administration, data analysis, and report writing and presentations. The MCPP initiative holds annual focus groups between survey administrations with all micro-communities and recently implemented virtual community–police restorative dialogues to engage community and police in discussing the findings of the Seattle Public Safety Survey and real-time public safety concerns. The MCPP initiative and the Seattle Public Safety Survey have evolved from a grassroots implementation in 2014 to an institutionalized and integrated part of SPD practice. Seattle Public Safety Survey data is included on the public-facing data dashboard and the MCPP research team is included in SeaStat (SPD's version of CompStat) (for a detailed explanation about the survey design and methodology, see Helfgott and Parkin, 2016, 2018, 2020; Parkin and Helfgott, 2020).

The Seattle Public Safety Survey is one component of the MCPP. The Seattle Public Safety Survey is a non-probability survey translated in 11 languages administered annually since 2015. The survey is administered through broad reach-out at the precinct and micro-community levels through email, social media, media, and physical distribution of flyers citywide. The survey is intentionally designed so that all community members who live and or work in Seattle have an opportunity to take the survey. Results are statistically weighted by city demographics. Residents are asked their concerns about crime and public safety and perceptions of neighbourhood-level quality of life elements—police legitimacy, fear of crime, social cohesion, social disorganization, and informal social control. Questions about over-policing, under-policing, and police capacity are included in the survey, such as, 'On a scale from 0 to 100, with 0 being strongly disagree and 100 being strongly agree, to what extent do you agree with the following when thinking about the Seattle Police Department and its officers?' '. . . There is enough Seattle police officer presence in my neighborhood.' Another type of question asks, 'What, if any, are current public safety and security concerns in the neighborhood where you live and/or work?' and includes both 'over-policing of neighborhood' and 'under-policing of neighborhood' as options. For the second two questions, respondents are presented with a dichotomous option to either agree or disagree that under-policing or over-policing is a public safety concern in their neighbourhood. Data are drawn from nine micro-communities (neighbourhoods) in the East precinct—Capitol Hill, Central Area/Squire Park, Eastlake-East, First Hill, Judkins Park/North Beacon Hill, Madison Park, Madrona/Leschi, Miller Park, Montlake/Portage Bay. Survey data are available starting in 2015. Results from the 2015 survey from 7,286 respondents who live and/or work in Seattle were used in this analysis.[5] Community preference is more challenging to model since these types of data are captured in an infrequent and relatively static form, and are linked to fixed geographic aggregates, as compared to the real-time and location-specific AVL and CAD log data. We will rely on visual comparison of community preference with the other data types.

Guiding hypotheses

It stands to reason that the spatial distribution of police presence (in the form of AVL pings) should

[5] We recognize that the two-year lag between the AVL and CAD data (2013) and the survey data (2015) is not ideal, but we believe these data are still useful for conceptual/proof-of-concept purposes.

be explained by public demand (calls for service), enforcement strategy (on-view activity), and community preference (perceptions regarding police presence). If a particular location has a high level of police presence but low levels of public demand, this could be a potential indicator of over-policing. Similarly, where a concentration of police presence would be expected but not observed, an opportunity for crime control treatment may yet to be discovered. Lastly, although we cannot assess this directly due to the time-lag between the data, there should be a proximal relationship between police presence and public attitudes towards the police. Therefore, we posit three hypotheses:

> H_1: Neighbourhoods with high levels of actual police presence, low levels of public demand, and high levels of enforcement strategy will have community preferences that support less police presence.
>
> $H_{2:}$ Neighbourhoods with low levels of actual police presence, high levels of public demand, and low levels of enforcement strategy activity will have community preferences that support more police presence.
>
> H_3: Neighbourhoods with levels of actual police presence that are relatively equivalent to the levels of public demand and enforcement strategy within them will have community preferences that indicate a satisfaction with current policing levels.

Modelling strategy

Our approach was to begin by determining the location of study (in this case, the East Precinct), and limiting the data to that location and for the specific time period of study. Some initial exploration of point data and computation of spatial statistics was performed in order to understand the spatial distributions. This was followed by kernel density estimation for the three types of data being explored. We used similar parameters for the density layers in order to facilitate re-classification and potential combination. We then identify the highest density locations for the different data types, and map those locations in order to demonstrate where high presence, demand, and strategy may or may not coincide. Finally, we overlay these data layers on the community preference data. We anticipate that areas with high demand and enforcement strategy will generally have high police presence, but where there is high presence without corresponding demand or strategy there may be potential over-policing.

Results

Figure 1 depicts the AVL point data in the East Precinct of the SPD during the 2-week period. As can be seen, during the 2-week period officers drove on almost every street within the Precinct. While it might be possible to identify some degree of clustering here, it is of course very difficult to do so at the Precinct scale and there is much overlap because vehicle locations are generally constrained by roads and parking areas. The temporal component is also aggregated here. But the visualization is useful for confirming that police vehicles during the 2-week period did essentially cover the entire Precinct to some degree and the areas that were not pinged are low-density residential streets.

To visualize clustering of AVL point data, we generated a kernel density layer using 50-foot cells and a 230-foot bandwidth.[6] The density layer in Fig. 2 is symbolized using 1 standard deviation

[6] This bandwidth was determined using the default method implemented by ArcGIS, which is an adaptation of Silverman's (1986) rule and seeks a radius that is insensitive to spatial outliers but also avoids the 'ring around the points' phenomenon that can occur with too narrow a radius. The average city block length in Seattle is 240 feet, so in practical terms the default bandwidth used here is approximately one city block (which seems reasonable for understanding the density of AVL data at a particular location). One might also use local tests for spatial clustering such as the Getis-Ord Gi* statistic (see Kalinic and

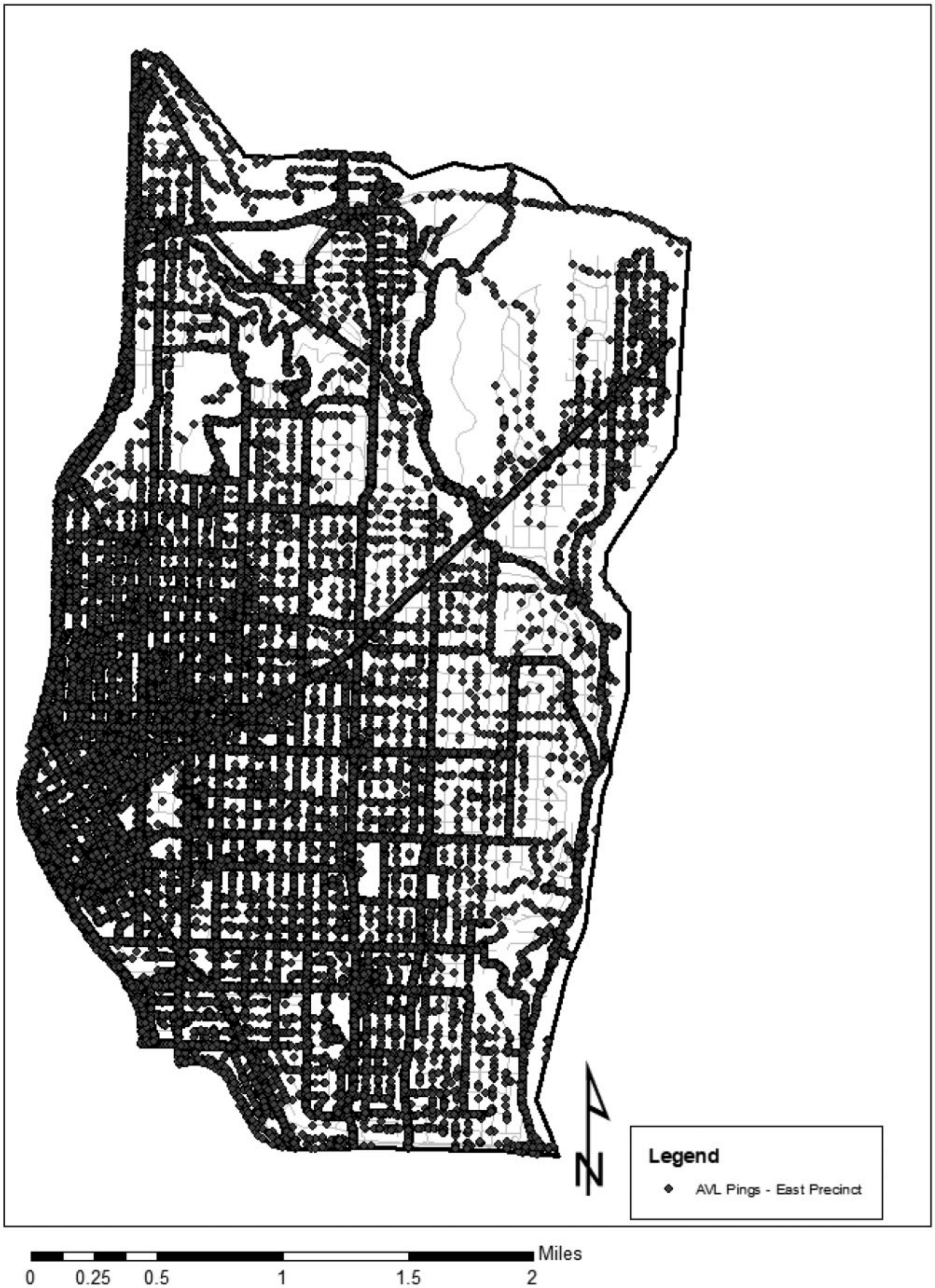

Figure 1: AVL point data, East Precinct, two week study period ($n = 372{,}804$)

(SD) breaks and depicts locations where there is greater estimated density of AVL point data. As can be seen, there are some areas where police presence is clearly more concentrated. One

Krisp, 2018), although more research is likely needed to determine appropriate applications with AVL data; we thank an anonymous reviewer for this suggestion.

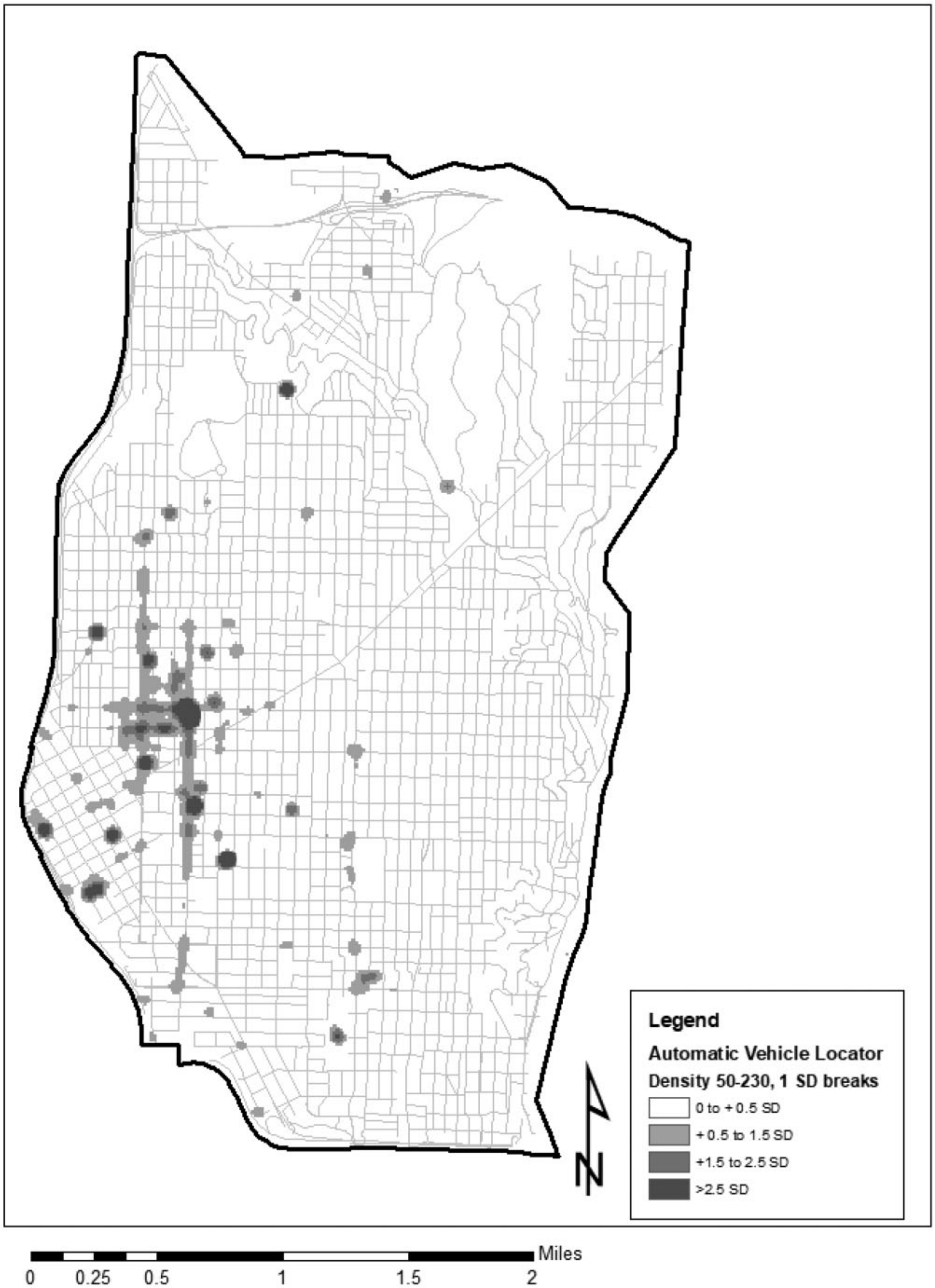

Figure 2: KDE for AVL data (50 ft cells, 230 ft bandwidth), 1 SD symbology

challenge made evident here is that police presence is 'structural' at certain locations such as the East Precinct Headquarters (which is surrounded by the largest density spot), where police vehicles are routinely departing and returning. Also, the higher density streets represent blocks with a relatively large number of apartment complexes and retail establishments, particularly those with restaurants and establishments serving alcohol.

We next examined the calls for service and onview data using the same methods and parameters. Figure 3 presents a density layer for the calls for service data, while Fig. 4 presents a density layer for onview activity.

For each of the three layers examined thus far (police presence, public demand, and enforcement strategy), we re-classed the raster layers using 1 SD breaks and display the upper-most category (mean + 2.5 SDs) for each in Fig. 5. The colour blue is used to depict areas of high police presence; green depicts areas with high public demand; and orange depicts enforcement strategy. As can be seen, there are some areas of overlap but also several areas where the three elements are distinct. The location of the East Precinct Headquarters is noted in the map, as are three locations of high presence that are associated with hospital parking.

Red circles are positioned around four locations where there is high density of police presence, but low public demand and enforcement strategy, and no immediately obvious structural explanation (such as a police facility, hospital, or other node of police presence). Starting with the northernmost circle, further investigation reveals that this is the parking lot associated with a private elementary (K-8) school. This may indicate the presence of officers at the school for an educational or enforcement purpose; alternatively, it could be an area where officers park to eat lunch, write reports and perform other administrative tasks, or rest. Moving south to the middle-two red circled areas, the first is a parking area located behind a strip of restaurants as well as a prominent corner coffee shop, adjacent to a university campus. The second is another parking lot associated with a university recreational facility. This parking lot has historically been used by the SPD as a staging area for the management of large public demonstrations, and officers are familiar with the location as a safe place to park when writing reports or needing a break. Finally, the southernmost red circled area is the parking lot of a public middle school. Again, this may indicate the presence of officers at the school for an educational or enforcement purpose, or for alternative reasons already noted. Collectively, these areas identified as high police presence demonstrate a potential challenge with the use of AVL data, in that some masking of locations or greater selectivity may be necessary. While we have been somewhat optimistic in our assessment of police presence at these locations, it must also be acknowledged that AVL data may identify excessive or inappropriate police presence (such as sleeping while on duty or engaging in other problematic behaviours).

We now try to place these data within the context of the Seattle Public Safety Survey data that bear on community preference. Figure 6 includes the survey data (shaded areas) regarding the over-policing question, and includes the high presence, demand, and strategy layers. The percentage of residents indicated that the SPD is over-policing their neighbourhood ranges from less than 1% up to 18%, though this was only for one neighbourhood. Two neighbourhoods only had 1–3% of respondents identify over-policing as a public safety concern, and six had less than 1%. There does not appear to be much correspondence between the high activity measures and the attitudinal data. The neighbourhood with the highest percentage of residents who stated that SPD is over-policing in the neighbourhood had few indicators of increased police presence in the area. However, this result could be an artefact of the survey data as this neighbourhood had a low response rate compared to the other areas resulting in a higher sensitivity to outliers in the data. Keeping in mind the time-lag between the AVL/CAD data and the survey data, it may be the case that these measures are not time-stable and police presence may have been very different at the time the survey data were collected.

Figure 7 switches to the under-policing question (the percentage of residents indicating that the

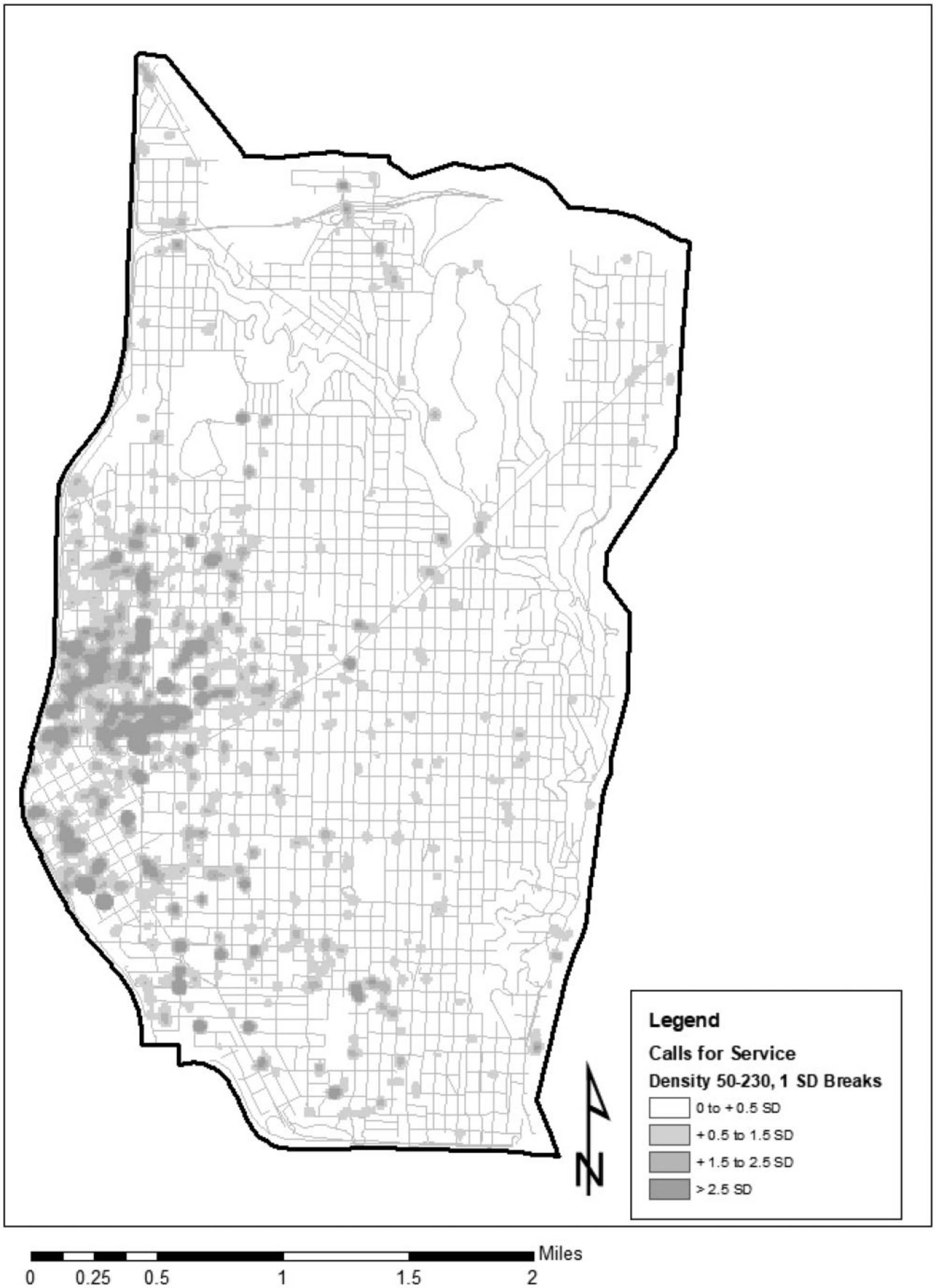

Figure 3: KDE for calls for service data (50 ft cells, 230 ft bandwidth), 1 SD symbology

SPD is under-policing their neighbourhood ranges from 10% to 45%).For these results, areas with relatively more clusters of police activity, calls for service, and onview activity have a minimum of 29% of survey respondents in those neighbourhoods indicating their communities are

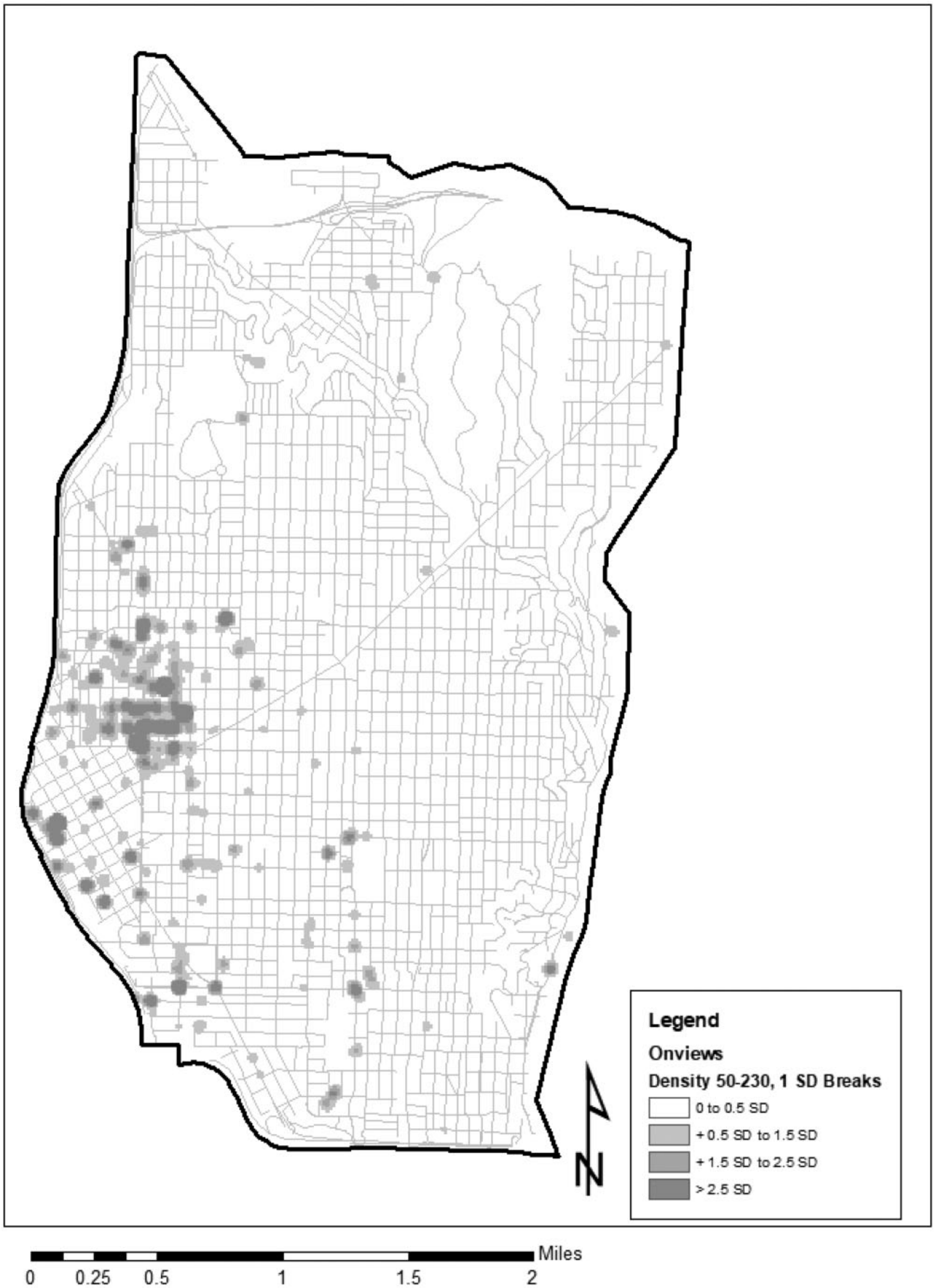

Figure 4: KDE for onview data (50 ft cells, 230 ft bandwidth), 1 SD symbology

underpoliced. Although, once again, the patterns are not uniform as communities with little or no clustering of police activity have similar survey results. Interestingly, survey respondents for communities in the northern portion of the North Precinct have little or no clustering of police activity

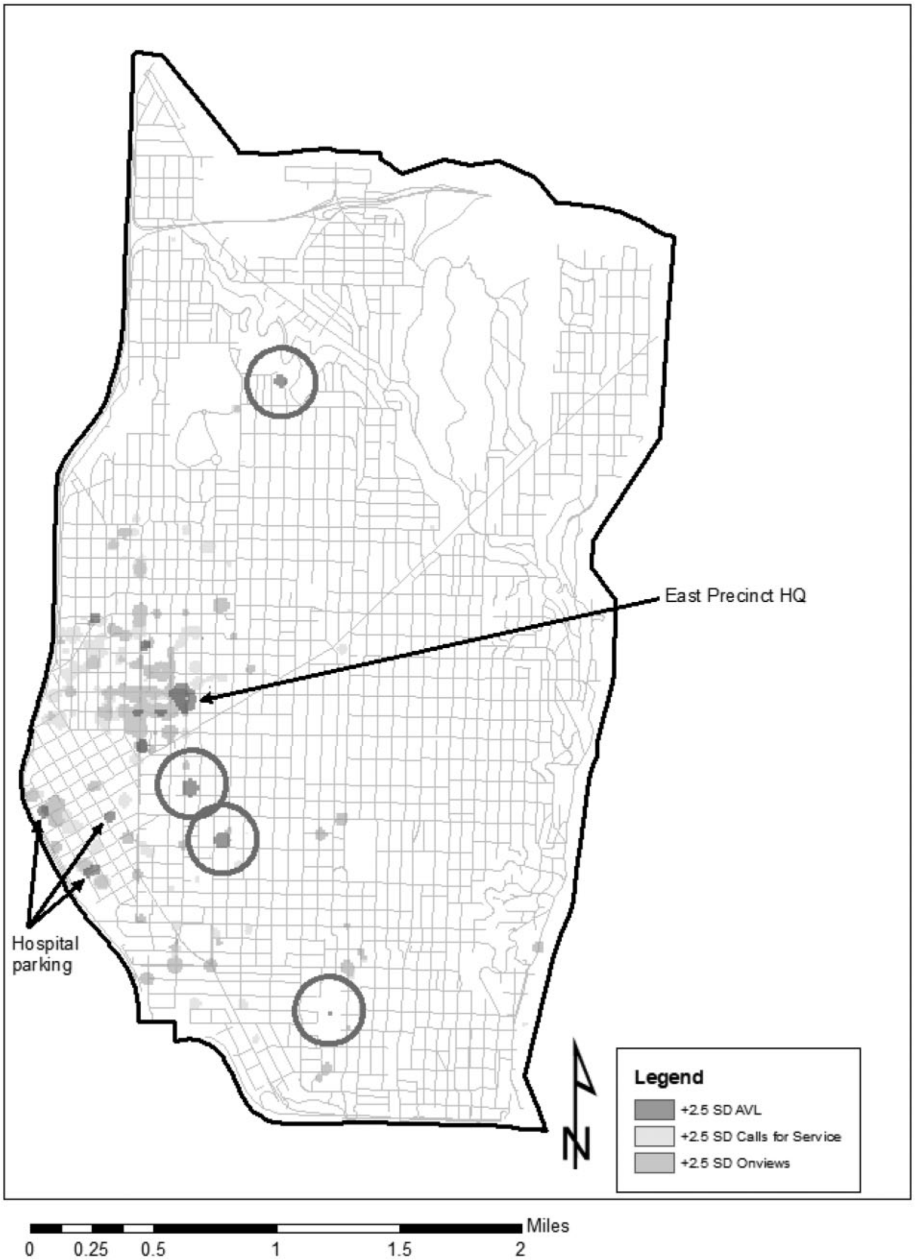

Figure 5: Overlay of re-classed KDE layers showing high presence (AVL), demand (CFS), and strategy (onviews), with red circles highlighting four areas of high presence with low demand and onview activity.

and were less likely, although not by much (22–29%), to indicate that under-policing was an issue.

Figure 8 maps the answers to the final question, which measures the average response, on a scale from 0 to 100, for how much a respondent agrees that there is enough police presence in their neighbourhood (0 no agreement, 100 full agreement). For residents indicating that there is

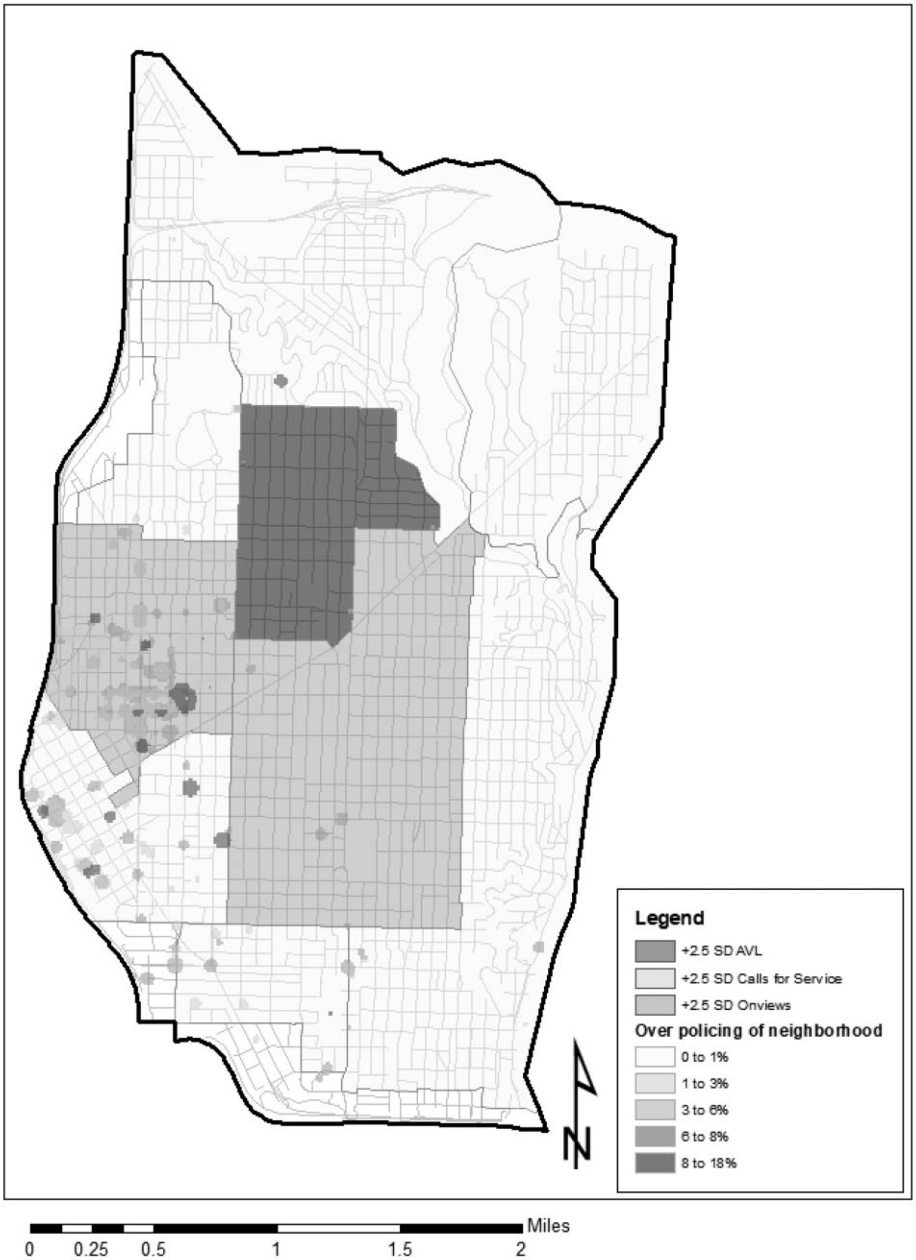

Figure 6: High presence (AVL), demand (CFS), and strategy (onviews), overlaid on level of agreement that SPD is over-policing neighbourhood.

enough SPD presence in their neighbourhood, there is a range from 35 to 60. When overlayed with the clusters of AVL, calls for service, and onview data, the neighbourhood on the west side of the East Precinct with the vast majority of clustered police activity, including calls and patrol at hospitals, shows an average survey response of 38–46 on the scale of 100 for agreeing there is

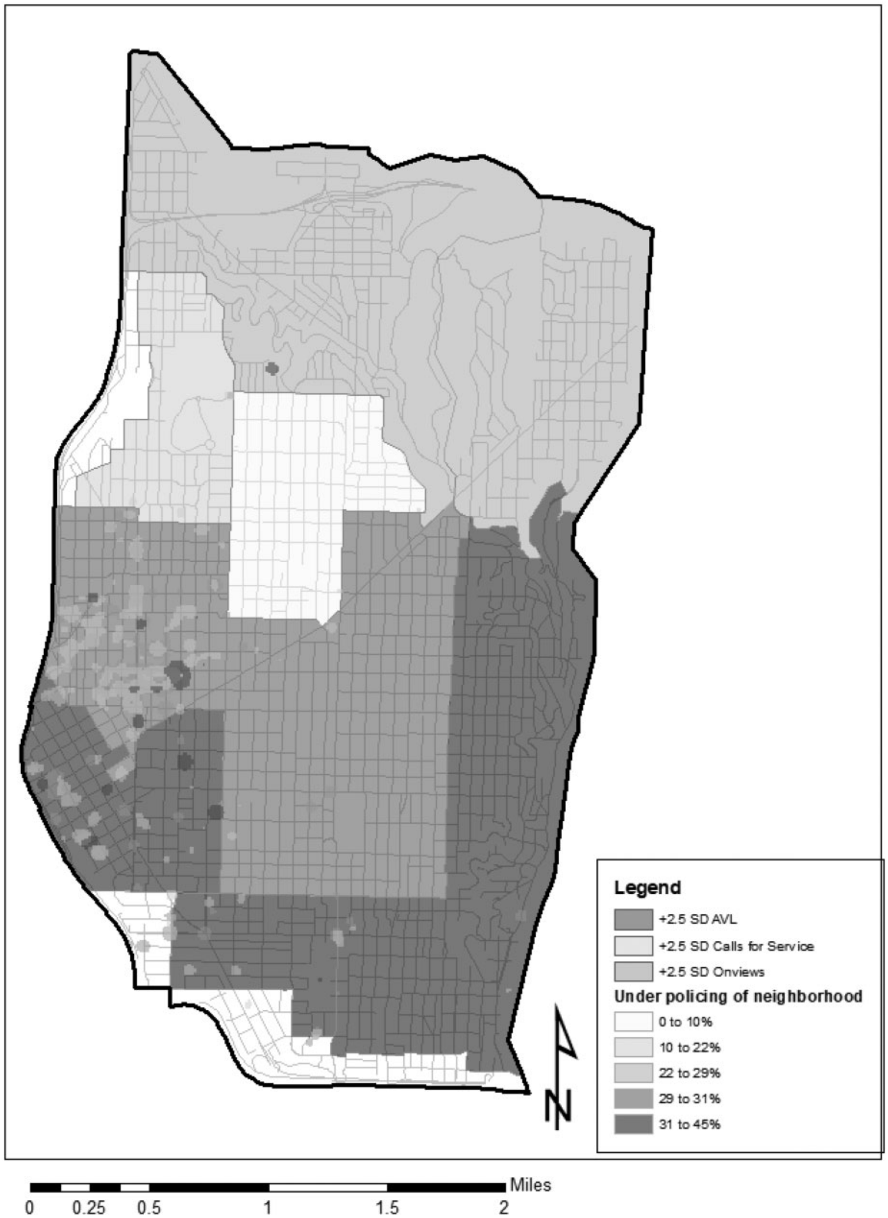

Figure 7: High presence (AVL), demand (CFS), and strategy (onviews), overlaid on level of agreement that SPD is under-policing neighbourhood.

enough police presence. The neighbourhood with the highest average of agreement with a range of 50–60 is in the centre of the Precinct with very little clustered activity, and the neighbourhood with the lowest level of agreement has clusters of calls for service and onview activity and limited AVL clusters. Also, although not in the highest tier, the neighbourhood with the highest

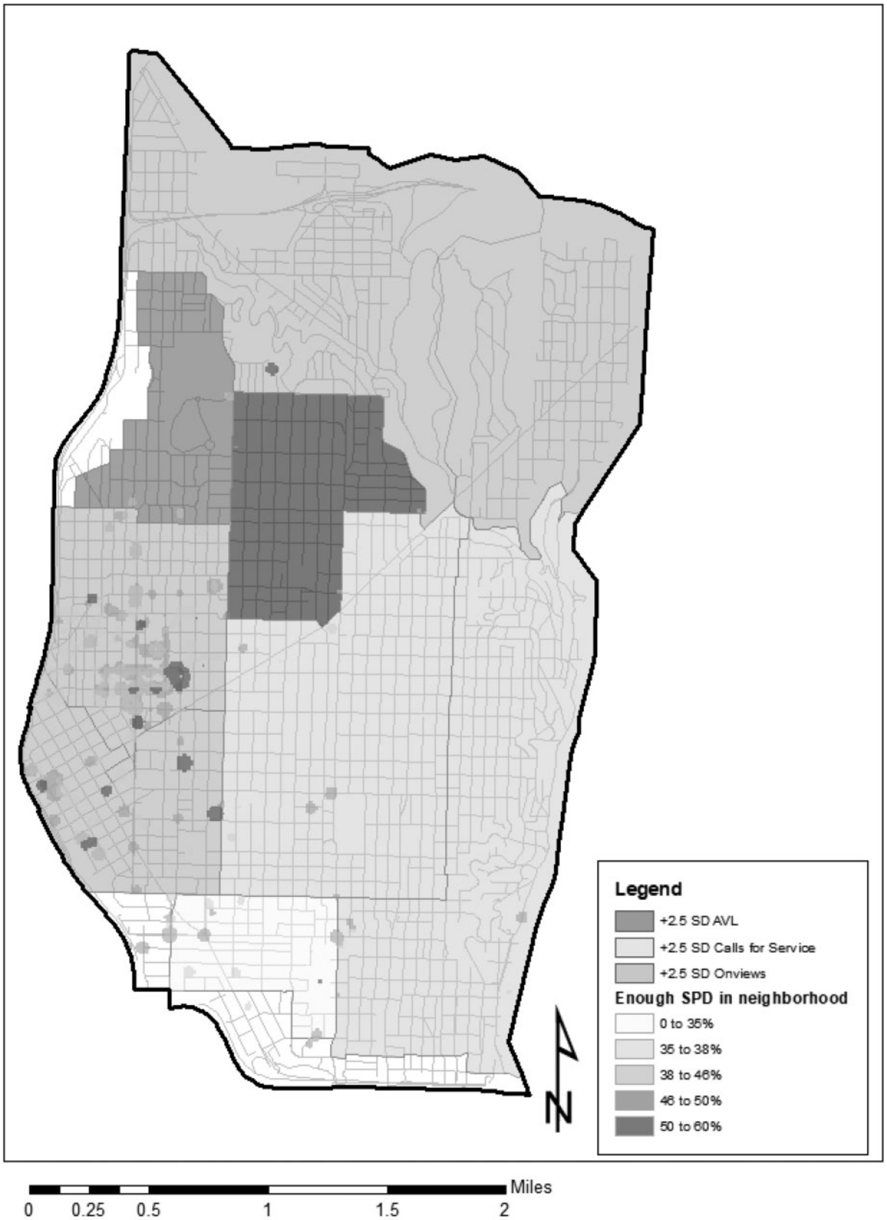

Figure 8: High presence (AVL), demand (CFS), and strategy (onviews), overlaid on level of agreement that there is enough Seattle police officer presence in neighbourhood.

density of activity for AVL, calls for service, and onview activity has average level of agreement that there is enough SPD presence in their neighbourhood.

Discussion

Returning to our hypotheses, we find weak support for our first hypothesis that stated neighbourhoods with high levels of actual police presence, low levels of public demand, and high levels of enforcement strategy will have community preferences that support less police presence. Partly, this is because there were no communities that fit these criteria. In fact, specific to over-policing, most communities had 0–1% of respondents selected over-policing as a public safety concern. Two communities had 3–6% identify over policing as a concern. Interestingly, in one these communities, there were many clusters of calls for service, onview activity, and police presence. Perhaps elevated police presence, regardless of need, impacts the public's perception of whether the community is over-policed. In the second community, there were few clusters specific to onview activity and calls for service with no clusters of police activity. This community, however, has historically been the home to the city's largest Black population. One hypothesis to explain this could be that regardless of what police activity occurs, a history of negative relationships with law enforcement in the community drives perceptions of whether a community believes they are being over-policed, regardless of the actual activity on the ground.

We find partial support for the second hypothesis that stated neighbourhoods with low levels of actual police presence, high levels of public demand, and low levels of enforcement strategy activity will have community preferences that support more police presence. There are several neighbourhoods that have clusters of calls for service and onview activity, with no or few clusters of police activity and had 31–45% of respondents state that under policing in their community was a public safety concern. Although, there also were neighbourhoods with 31–45% of respondents stating under-policing was a public safety concern with several clusters of police activity—albeit most of these were hospital emergency rooms. The neighbourhood with the most clusters of police activity not related to hospitals or the precinct headquarters also had the most number of calls for service and 29–31% of respondents identifying under-policing as a public safety concern. These results also provide insight into the final hypothesis, which stated that neighbourhoods with levels of actual police presence that are relatively equivalent to the levels of public demand and enforcement strategy within them will have community preferences that indicate a satisfaction with current policing levels. In some ways, the types of neighbourhoods that have a disproportionate number of calls for service, onviews, and police activity, show that under-policing, not over-policing, is a concern for residents when high levels of criminal activity are occurring, regardless of the amount of police presence or how proactive they are when in the community.

Taken together, these results support the utility of a real-time data analysis tool that can map law enforcement activity, calls for service, onview activity, and public perceptions of whether their communities are being over- or under-policed—both of which if they do not match the expectations of the public can negatively impact police legitimacy and trust. The data show that although not uniform across all neighbourhoods, some communities aligned with our expectations, that perceptions of over- or under-policing could be explained by the amount of potential criminal and police activity. However, other communities did not support the hypotheses. For example, one community, which has historically been the home of the city's largest Black community had relatively higher levels of perceptions of being over-policed, although also having relatively high levels of feeling under-policed. In other cases, affluent communities with no clustering of calls for service, onviews, or police activity had relatively high levels of respondents perceiving the community was over-policed. These results could present evidence that in some cases, criminal and police activity can drive the public's perception about whether they are being under- or over-policed, but in other neighbourhoods, it is the expectations of the community, regardless of the reality of crime and policing, that drives these perceptions.

Business intelligence in the policing context does not need to focus, strictly, on accountability. Although accountability applications tend to directly address issues of trust and legitimacy, an agency that learns to engage in real-time or near-real-time data insights would naturally promote a sense of deliberate, purposeful management, if not outright confident control of forces. CompStat, or as it is referred to in the City of Seattle, 'SeaStat,' and the management tools (e.g. reports, dashboards, intelligent decision support processes) used to monitor and respond to emergent patterns in the operation, are designed to promote engagement on the part of managers and commanders, by fostering a sense of 'data curiosity.' In this context, insights do not definitively identify problems; rather, insights generated from the distillation of large volumes of noisy data are intended to direct a user to dig deeper and understand the observation.

Within the context of processed AVL, as discussed above, the implications are myriad. For instance, an apparent overconcentration of presence might indicate over-policing, as hypothesized, or a potential operational security vulnerability (e.g. ambush risk). Diagnosing the underlying disease, from observations of the symptoms, aids in accepting the corrective action. This process of acceptance can only be developed through constant engagement. This is the philosophy underlies the CompStat model and is further enhanced by constant contact and ever more sophisticated methods of analysis.

The utility of the SPD MCPP initiative and the Seattle Public Safety Survey in examining over-policing in neighbourhoods is noteworthy. The Seattle Public Safety Survey was designed as a collaborative academic–practitioner initiative to collect annual data to inform the SPD MCPP and to increase community–police engagement and public safety. The longevity and institutional integration of the MCPP and the ongoing annual Seattle Public Safety Survey offer Seattle rich community perception data not available in other cities. Ongoing measurement of over-policing in neighbourhoods is one of the many ways the Seattle Public Safety Survey data can be used to direct police resources and city services to address quality of life elements of public safety in Seattle.

Limitations and future research

Several limitations of this research should be noted. First, the data only measure police activity over a limited time period of 2 weeks and static survey results. Also, the survey data, which is a non-probability sample taken across the city during a 45-day period, was collected 2 years after the AVL, calls for service, and onview activity data. Although we believe there is still value for conceptual/proof-of-concept purposes, this time difference could have an impact on the results as the policing and crime activity occurring within a respondent's neighbourhood immediately prior to or during the period that the survey was available could be different than the activity capture 2 years prior. Future research should attempt to collect and utilize data that is collected contemporaneously or the police activity and calls for service data immediately prior to the survey data being collected. Future research should expand to larger geographic areas wither including more of Seattle or additional jurisdictions and explore additional spatial socio-demographic and criminal justice data. There is much work to be done in understanding better ways to model AVL data and understanding spatial correlates.

In addition, our community perceptions of over- and under-policing were based on community responses to a citywide survey. Perceptions of policing could be impacted by the timing of the survey, the survey population, and the recentness of police contact with the survey respondent. Therefore, future research should develop ways to measure community perceptions of over- and under-policing that may not be as dynamic and could provide stable estimates across time. With the important caveat about time lag in the present study, when a disconnect is observed between perception and police data this can serve as a useful mechanism to initiate discourse with the communities served and try to find out how policing can be better tailored in those communities, or to identify where greater outreach may be necessary.

We should also note that it is reasonable to raise questions about the broader practicality of the approach we propose to assessing over- and under-policing—that is this something for which we would anticipate widespread use given the resources and capabilities available in most police departments? While larger departments having crime analysts engaged in mapping would likely have the technical resources and skills or could reasonably acquire them, it is unlikely that smaller departments would have those resources, the data, or necessarily the need for this type of analysis. However, as research develops on use of AVL data for these purposes, and if it proves useful, then to the extent that the data are available it is possible that common Computer Aided Dispatch/Records Management System vendors could incorporate dashboard tools into their systems to integrate AVL and CAD data, which would make broader use more practical.

Conclusion

On balance, this study suggests that there is great potential to learn about police behaviour as well as the effects of police presence and public attitudes towards the police through analysis of AVL records and other GPS-based monitoring data. To be sure, there are reasonable privacy and safety concerns over the access and use of these types of data. But as the utility of the data become more apparent through research and development—and importantly, demonstration to police executives—we believe it will be possible to address and satisfy those privacy and safety concerns. There is great promise for addressing the problem of over- and under-policing and restoring or enhancing public trust and confidence in the police, and that alone should serve as a strong incentive for police researcher–practitioner partnerships aimed at exploring these data.

Beginning in the fall of 2021, the SPD will be one of the first police services in the United States to engage a measure of police performance other than the crime rate. The Equity Accountability and Quality forum, modelled after CompStat, will begin to use an operationalization of the method reported here in the form of hot and cold spots of policing, by precinct and watch. This programme is designed to foster a culture of continuous improvement around a more sophisticated approach to measuring the direct and indirect impacts of policing, and will attempt to bring full circle the cycle of innovation exemplified by this practitioner–academic collaboration.

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