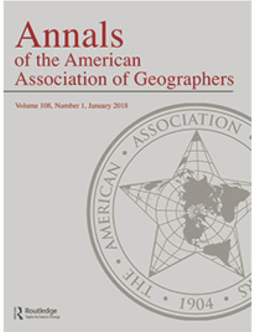

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Predictable Policing: Predictive Crime Mapping and Geographies of Policing and Race

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This article draws on critical geographic engagements with policing and race and geographic information systems (GIS) to investigate the implications that predictive crime mapping has for racialized modes of urban policing. Focusing on the Chicago Police Department (CPD), it analyzes collaborations between geographic information scientists, crime experts, and police who have recently begun integrating temporal data into GIS-based maps to predict when and where future crimes will occur. The article builds the case that predictive crime mapping further entrenches and legitimizes racialized policing as it (1) rearticulates police data sets as scientifically valid and (2) correlates those data with other geocoded information to create new rationalizations for controlling racialized districts through differential policing practices. The article uses a mixed-methods approach that includes analysis of open-ended interviews with computer scientists involved with the CPD's Predictive Analytics Group and city technical documents to explain the recursive relation between GIS-based knowledge production and racialized policing. The article casts into relief the central role that the production of geographic information plays in current modes of racialized policing and how this contributes to the ongoing racial differentiation of urban geographies. *Key Words: Chicago, GIS, police, predictive policing, race.*

本文运用警备和种族的地理涉入, 以及批判地理信息系统 (GIS), 探讨预测犯罪製图对于城市警备的种族化模式之意涵。本文聚焦芝加哥警察局 (CPD), 分析地理信息科学家, 犯罪专家, 以及警察之间的合作, 他们最近开始将时间数据整合进根据 GIS 的地图, 以预测未来的犯罪将在何时何地发生。本文将论证, 预测性的犯罪製图进一步确立并正当化种族化的警备, 因其 (1) 再度表达警察数据集是具有科学根据的, 以及 (2) 将上述数据连结其他进行地理编码的信息, 为透过差异化的警备行为来控制种族化的地区创造了崭新的合理化。本文运用混合方法取径, 包含对参与芝加哥警察局预测分析团体的计算机科学家的开放式访谈之分析, 以及城市的技术文件, 以解释根据地理信息系统的知识生产与种族化的警备之间的递归关係。本文清晰化地理信息生产在当前的种族化警备中的核心角色, 及其如何导致城市地理的持续种族差异化。 *关键词： 芝加哥, 地理信息系统, 警察, 预测性警备, 种族。*

El artículo se basa en enfrentamientos geográficos críticos con la vigilancia policial y la raza, y en los sistemas de información geográfica (SIG) críticos para investigar las implicaciones que tiene el mapeo predictivo del crimen para los modos racializados de la vigilancia policial urbana. Centrando la atención en el Departamento de Policía de Chicago (CPD), el artículo analiza las colaboraciones entre científicos de información geográfica, expertos en criminalística y la policía que hace poco empezaron a integrar datos temporales en mapas basados en SIG para predecir cuándo y dónde ocurrirían los crímenes futuros. El artículo construye el caso de que el mapeo predictivo del crimen atrinchera aun más y legitima la vigilancia policial racializada por cuanto ese mapeo (1) rearticula conjuntos de datos policiales como científicamente válidos, y (2) correlaciona esos datos con otra información geocodificada para generar nuevas racionalizaciones que ayuden a controlar distritos racializados por medio de prácticas de vigilancia policial diferenciales. El artículo usa un enfoque de métodos mixtos que incluye análisis de entrevistas de final abierto con científicos de computación involucrados con el Grupo de Análisis Predictivo del CPD y documentos técnicos de la ciudad para explicar la relación recursiva entre la producción de conocimiento basada en SIG y la vigilancia policial racializada. El artículo destaca el papel central que juega la producción de información geográfica en los modos corrientes de vigilancia policial racializada y cómo eso contribuye a la actual diferenciación racial de las geografías urbanas. *Palabras clave: Chicago, SIG, policía, vigilancia policial predictiva, raza.*

In 2010, the Chicago Police Department's (CPD) Predictive Analytics Group was analyzing 911 data and reported that a shooting would likely take place on a particular block on the South Side that day. Shortly after, the group's director received a text message informing him of gunfire on the exact block indicated in the report. The shooting occurred three minutes after the report was printed (Main 2011). The anecdote

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exemplified a recent trend in police departments where geocoded crime statistics are coupled with temporal data to predict when and where crimes will occur.

Indeed, a growing number of GIScientists, crime experts, and urban police departments are using geographic information systems (GIS) and predictive analytics to shift police emphasis from "targeting classes of people or geographic regions to targeting specific individuals and more precise locations" (Rosenblat, Kneese, and Boyd 2014). Nearly a dozen departments have received federal funding to develop GIS-based "crime forecasting" methods to map prospective crimes over the past five years (Tompson and Townsley 2009; Uchida 2009; Beiser 2011; Thompson 2011; Greengard 2012; Vlahos 2012).[1] In an age of heightened tension between police and racialized communities, however, critical questions emerge: Do predictive mapping practices have meaningful impacts on racial profiling or the widespread criminalization of the racialized poor? What do these practices reveal about relations among spatial statistical analysis, geovisualization, and racialized urban geographies?

Focusing on the CPD, this article builds the case that predictive crime analysts' reliance on official crime statistics works to further entrench and legitimize the geographic knowledge and practices of racialized policing. It chronicles how, in building an entire GIS-based system around these data, the police intuitions and policies that are fundamental to racialized policing are validated anew. And this validation continues despite the decades of scholarship have shown the sociospatial patterns in official crime data to be functions of extracriminological factors. In fact it is well established that the stark racial and geographic disparities in crime data are effects of invidious law making (Sample and Philip 1984; Ermann and Lundman 2002), discriminatory policing policy (Hall et al. 1978; Sutherland and Cressey 1978; Wilkins 2013), and police officer bias (Skogan 1975; Booth, Johnson, and Choldin 1977; Decker and Kohfeld 1985; Gove, Hughes, and Geerken 1985). This article excavates the way in which these racialized infrastructures embedded in official crime data sets shape predictive crime mapping and how the maps reciprocally legitimize those data sets through their ostensibly scientific presentation. To do so, it builds on geographic engagements with policing, race, and urban governance, particularly those that elucidate links between hyperaggressive policing, the racialized poor, urban disorder, and neoliberal urban governance (N. Smith 2001; MacLeod 2002; Mitchell 2003; Wilson 2005; Gilmore 2007; Beckett and Herbert 2011; Vitale and Jefferson 2016). My analysis draws on how these works articulate urban police departments' increasing entanglement with managing the disorders that afflict racialized "problem populations" (Spitzer 1975) or economically superfluous groups that are unable or unwilling to generate value in primary labor markets and how this is linked relationally to black and latinx overrepresentation in the criminal justice system. Although this scholarship casts considerable light on how police differentially target racialized sectors of cities, the geographic knowledge and information essential to this regime is seldom scrutinized.[2]

In rectifying this deficiency, the article draws on critical GIS scholarship. Fundamental to these works is a critique of the unchecked positivism that characterizes the bulk of governmental GIS practices and the ways in which these practices translate into social differentiation and marginalization (Taylor 1990; Bondi and Domosh 1992; N. Smith 1992; Curry 1993; Lake 1993; Sheppard 1995, 2005; Pickles 1997; Kwan 2002a; Schwanen and Kwan 2012). Government GIS practices draw on bureaucratic databases and quantitative methods that militate against critical, qualitative, and structural modes of geographic knowledge. As a consequence, the corresponding GIS visualizations ensure that social problems are portrayed and interpreted in ways that are only commensurate with preexisting policy frameworks (Sheppard 1995; Yapa 1998). Moreover, critical GIS scholars show how GIS-aided government practices are enmeshed in relations of social power, particularly in terms of creating and controlling categories of marginalized people (Curry 1993; Lake 1993). As such, GIS practices are bound up with turning human subjects into manageable objects, most often in accordance with certain political economic ends. But insightful as these works are, scant attention is paid to the implications such GIS practices have for constituting and controlling racialized populations and places. Thus, building from insights in critical GIS, my analysis seeks to excavate the relational links among precrime mapping, geographic knowledge, and differential social control of negatively racialized populations and places in Chicago.

By putting geographic research on policing and race into discussion with critical GIS, this article elucidates two ways in which precrime maps reinforce the differential policing of racialized people and places. For one, although Chicago officials tout predictive crime mapping as a scientific approach to devising police policy that "meld[s] urban science and data analytics" (Urban Center for Computation and Data [UCCD] 2013), the entire system is built atop data sets compiled by nonscientists[3] operating within a system of racialized policing. Despite the CPD's notoriously problematic data collection practices (McEwen 1996; ACLU 2015, 2016; Andonova 2016), the predictive crime analysts' uncritical acceptance of police data works to legitimize both the data sets and the police practices that produce them. For another, the article investigates the way predictive crime analysts correlate police data with other geocoded information bits and how this produces new rationalizations for differentially policing racialized districts. The net result is that predictive crime mapping rearticulates police data sets as scientifically valid and produces new geographic knowledge and geovisualizations that work in the service of the ongoing and differential police control of racialized districts. These findings contribute to critical geography by revealing the increasingly prominent role GIS are playing in differentiating urban space along axes of race and class and legitimizing forms of social exclusion and marginalization.

My analysis focuses on the CPD Predictive Analytics Group to explain the recursive relations between GIS-based knowledge production and racialized policing. Chicago offers a unique case to examine the implications of this development, as it has been a leader in crime prediction for nearly a century (Harcourt 2006), is one of the earliest cities to apply GIS to crime mapping (Maltz, Gordon, and Friedman 2000), and was recently censured for its "history of racial disparity and discrimination" (Police Accountability Task Force [PATF] 2016). The article uses a mixed-methods approach, drawing on interview data with computer scientists involved with the Predictive Analytics Group and city technical documents on GIS crime mapping. Interviewees were selected by snowballing techniques. Recorded interviews with former and current members of the group and broader police department were examined for mention of predictive analysis, crime mapping, police tactics, and race. Additionally, archival materials included city documents from Chicago's Municipal Reference Collection, articles from local newspapers, and technical reports from computer scientists involved with the Predictive Analytics Group.[4]

Racialized Policing and Geographic Information Production

Several geographers and geographically sensitive scholars explore relations among policing, space, and race. These studies retrace how hyperaggressive policing and penal policies have emerged as leading instruments for managing the social problems that rack the racialized poor in redeveloping cities (N. Smith 2001; Herbert and Brown 2006; Wilson 2006; Gilmore 2007; Wacquant 2009; Beckett and Herbert 2011). Since the 1990s, geographers show, city governances vying to become magnets of consumption, finance, gentrification, and investment have fashioned policing policies designed to micromanage the public presence of problem populations and the disorder (e.g., crime, drug addiction, visible homelessness) that ails them (Mitchell 1997; N. Smith 1998; MacLeod 2002; Wilson 2006; Beckett and Herbert 2011; Walby and Lippert 2012). Emphasis is placed on the way police are mobilized to aggressively relocate economically superfluous labor fractions and signs of their indigence from city centers to predominantly racialized enclaves strewn across the periphery. Other geographers concentrate on the policing strategies that essentially contain these "problems" in marginal black and latinx areas (Jefferson 2015; Shabazz 2015). Both strands show that whereas social policy once played a central role in spatially containing these now redundant populations (Wilson 2005; Wacquant 2009), the criminal justice system, with police at the front edge, now bears the brunt of this task.

Although these works shed considerable light on the connections between regimes of policing, racialized geographies, and neoliberal urban restructuring, the role that the production of geographic knowledge has in this process remains largely unexplored. A notable exception is found in Herbert's (1996) work, which examines how place-dependent "normative orders" affect the way patrol officers establish and enforce territoriality. Herbert chronicles how police perceptions of different places are mediated by cultural codes that structure differential knowledge about patrol areas and encourage differential ways of controlling them. Moreover, cultural codes attached to blackness can activate policing practices marked by undue cautiousness, excessive morality, and ardent masculinity, which reinforce hyperaggressive policing in black neighborhoods.

These insights notwithstanding, the mechanisms by which these place-based, racialized normative orders are converted into technical geographic knowledge are virtually unexplored. In fact, the dynamic relation between the production of GIS-based information and the policing–race nexus has yet to be subjected to critical geographic analysis.[5] Since the mid-1990s, though, GIScientists, crime experts, and police have merged police data with GIS to create real-time, geographic representations of crime (Eck et al. 2005;

Zhang, Hoover, and Zhao 2014; Curtis et al. 2016). More recently, they have turned attention toward integrating temporal data to make crime maps predictive and pinpoint exactly where and when future crimes will take place (Gorr, Olligschlaeger, and Thompson 2003; Bowers, Johnson, and Pease 2004; Ratcliffe and Rentgert 2008; Gerritsen 2015).

Central to the evolution of GIS crime maps is the emergence of prospective "hot spots" of crime that, once geovisualized, have provided police executives positivist pretexts for preemptive policing. An influential early method was Ratcliffe and McCullagh's (1998) aoristic model, which weights geocoded crime events to probability estimates within a time window to estimate future crimes in given areas (also see Ratcliffe 2000). The method classifies maps into a binary surface of "hot spot" and "not hot spot" using statistical software and generates visualizations of "aoristic signatures" at the scale of hours, days, or months (Ratcliffe 2002). Similarly, Ratcliffe's (2004) "hotspot matrix" combines temporal weighting with GIS mapping to estimate probabilities of different types of crime each hour of a day within hot spot areas. The method creates a six-dimensional typology of hot spots: Three dimensions pertain to a hot spot's geographic characteristics (dispersed, clustered, hotpoint), and the other three pertain to its temporal signature (diffused, focused, acute). As a result, nine types of hot spots are recognized through this methodology, each designated for differential policing practices (see Ratcliffe 2004).

In a similar vein, crime analysts have employed a variety of clustering methods to identify temporal variances within hot spots and provide signposts for the differential policing among them. Nearest neighborhood hierarchical (Nnh) clustering routines are commonly used in CrimeStat GIS software to identify crime points aggregated around blocks, bars, and restaurants (Chainey and Ratcliffe 2005), drug sites and high-crime neighborhoods (Eck et al. 2005), and street segments and vacant lots (Herrmann 2015). H. Liu and Brown (2003) used a transition density model that incorporates data about a hot spot's features (e.g., average education level of residents, homeownership, household income, household size, land-use information, workforce characteristics, and more). The model is thus designed to "identify new potential hot spots or areas at risk that are not necessarily in the vicinity of existing crime locations" and provide police geographically precise locations to differentially "target patrols, direct surveillance, and conduct other operations to prevent crimes and enforce laws" (603).

Moreover, diffusion models are commonly used in predictive crime mapping to determine future crime patterns and aid police in deploying resources in an anticipatory fashion. Davies and Bishop (2013) took burglary and street network data to calculate previously burglarized street segments' attractiveness (e.g., lack of supervision) and centrality (user density). Once correlations between attractiveness and the probability of offense are determined, the model generates a primal representation of crime diffusion risk along street segments, which provides signposts for dispersing police patrols in a preemptive manner (see also Bowers, Johnson, and Pease 2004; L. Liu et al. 2005).

As thoroughly geographic as this incipient field is, it has yet to be subjected to critical geographic scrutiny. This lacuna is particularly salient as GIS have come to function as brain trusts for urban police departments across U.S. cities (Chainey and Ratcliffe 2005; Zhang, Hoover, and Zhao 2014; Curtis et al. 2016). Moreover, critical geographers elucidate the ways in which GIS are mobilized for reproducing hierarchical social relations (N. Smith 1992; Lake 1993; Sheppard 1995; Sieber 2000; Elwood 2002; Pickles 2004; St. Martin and Wing 2007; Ekbia 2009). Feminist geographers provide considerable insights into how government-based GIS practices impose masculinist norms on the populations and places they represent and thereby subjugate feminized subjects and modes of subjectivity to patriarchal values and objectives (Bondi and Domosh 1992; Lawson 1995; McLafferty 1995, 2002; Roberts and Schein 1995; Rocheleau 1995; Anderson and Smith 2001; Kwan 2002a, 2002b, 2008). Kwan (2002a) identified empiricist-positivist uses of GIS as expressions of knowledge-power, which can devalorize feminine categories and erase feminized subjects in the process. In light of this fecund scholarship, however, little has been done to explore how GIS help create and control racialized subjects. Although some scholars direct attention toward the uneven access racialized subjects have to GIS (Crutcher and Zook 2009), the role these systems play in constituting and controlling racialized populations is largely unknown. In what follows, I focus on the CPD to chronicle the implications that the production of GIS-based information has for racialized policing and the (re)production of racialized urban geographies.

GIS and Racialized Policing in Chicago

In Chicago, connections among GIS, geographic information, and legitimizing differential policing in racialized police districts coalesced during the late 1980s. It was then that city officials began extolling GIS for providing the CPD instant access to "accurate crime data for their beats, sectors or districts" and levels of spatial exactness unmatched by any policing technique (Daley and Rodriguez 1995; Daley and Weis 2007). Declarations of geographic precision notwithstanding, the CPD's embrace of GIS provided statistical justifications for a series of dragnet operations across racialized segments of the city.

As early as 1988, the CPD teamed with the National Institute of Justice (NIJ), the Chicago Alliance for Neighborhood Safety, and scholars from Chicagoland universities to implement the Microcomputer-Assisted Police Analysis and Deployment System (MAPADS). They first tested the system in the West Side's Austin neighborhood, a "community in racial transition" becoming overwhelmingly black and more deeply impoverished (Maltz, Gordon, and Friedman 2000). By 1990 it was categorized as 86 percent black and had 29 percent of its residents living in poverty (U.S. Census 2000).[6] The implementation of MAPADS was predicated on the belief that "maps are the only place where one can see everything that is going on in an areas. . . . Only on a map can the entire beat experience be put together and the pattern discerned from the individual incidents" (Maltz, Gordon, and Friedman 2000, xi). MAPADS combined geographic data (street, blocks, railroad tracks) with crime data (type of crime, location, time of occurrence) to generate "institutional memories" for police beats and deploy tactical units and patrol missions accordingly. Short-lived though it was, the department hailed MAPADS for offering "greater awareness of the beat's activity patterns and potential problems" and "beat-centered tactical planning" (Maltz et al. 2000, xiii, 64).

A similar initiative to MAPADS was launched in 1991, when the Illinois Criminal Justice Information Authority and officials from the CPD's Area 4 collaborated to devise a GIS-based mapping system to track the activity of the city's four major black and latinx gangs, including the Black Gangster Disciple Nation, Latin Disciples, Latin Kings, and Vice Lords (Block and Block 1993). Focusing on the territories occupied by these groups, the team geocoded the locations of homicides and gang-related incidents, which were in turn aggregated by community area. Gang turf and drug hot spots were derived from the data using Spatial and Temporal Analysis of Crime (STAC) software (Beta Version, Illinois Criminal Justice Information Authority, Chicago, IL, USA), which identified the densest clusters of incidents on a map, calculated a standard deviational ellipse fitting each cluster, and mapped both. In addition to drug markets, STAC identified liquor stores, parks, parking lots, public housing courtyards, school grounds, street intersections, and transit stops that were contiguous with black and latinx gang territories as criminogenic as well. In the end, gang mapping provided spatial statistical justification for police "targeting the causes of short-term or acute escalations in violence" throughout neighborhoods hosting the four gangs mentioned earlier (Block and Block 1993, 9).

From this point onward, the tendency found in state cartographical practice to mark more and more spaces for enhanced social control becomes evident (Pickles 2004). Gang mapping convinced beat officers, detectives, and high-level decision makers that easy to use and accessible computerized maps were groundbreaking tools for understanding and strategizing against crime (Rich 1996). It also gave city officials a new vocabulary for rationalizing the differential and hyperaggressive policing of racialized districts (Daley 1995; Daley and Rodriguez 1995). Thus, in 1995, the CPD implemented Information Collection for Automated Mapping (ICAM), which developed in conjunction with the launch of several prolonged policing initiatives in Black Belt neighborhoods.[7] ICAM's software generated maps at the scales of police districts, sectors, and beats and was celebrated by officials for pinpointing hot spots of criminal activity at unprecedentedly spatial resolutions. It quickly became the "linchpin of [a] whole strategy" (Rich 1996, 10), marked by the infusion of extra patrol forces in GIS-generated hot spots including bars, buildings, churches, schools, liquor stores, street segments, and street intersections showing statistical correlations with illegal activities (Daley and Rodriguez 1995; Rich 1996). ICAM was also pivotal in launching the CPD's School Patrol Unit in 1995, which deployed patrols using ICAM to "track and continuously evaluate specific student school problems" (Daley 1995).

The practical result of ICAM-aided law enforcement was an increase in the magnitude of the CPD's already racialized mode of policing. Whereas the rate of arrestees categorized as black and white held constant from 1994 to 1995 (70 and 30 percent, respectively), the total number of all arrestees increased by almost 30 percent (CPD 1995, 1996). In addition, the number of CPD arrestees under the age of eighteen

(72,969) relative to the total number of arrestees (305,242) marked a 5 percent increase from the year Daley first took office (Bureau of Justice Statistics [BJS] 2016a). Moreover, 12,207 more juveniles categorized as black were arrested in 1995 than in 1989, compared to 4,809 more juveniles categorized as white (BJS 2016a).

Irrespective of the precision geographic information at the CPD's disposal, the emergence of GIS crime mapping did not attenuate the department's differential criminalization of populations and places it categorized as black. The CPD's own arrest data for victimless crimes (vandalism, gambling, drunkenness, and disorderly conduct) between 1991 and 1999 showed remarkably consistent disparities between Chicagoans categorized as black and white. During this period, 70 percent of arrestees for these categories were classified as black compared to 29 percent white, with a standard deviation of less than a tenth of a percent (BJS 2016a). This translated into Illinois's prison population, the vast majority of which is drawn from the Chicagoland region (see Peck and Theodore 2008). In 1990, 60 percent of Illinoisans under state or federal correctional control were classified as black, 29 percent white, and 8 percent Hispanic (BJS 2016b). By 1995, the white fraction dropped to 24 percent, and the black fraction rose to 65 percent (BJS 2016b).[8] Inasmuch as GIS crime mapping had no significant impact on the differential criminalization of racialized populations and places, the data suggest that the maps merely reinforced and worked in tandem with the intensification of an already racialized regime of policing.

Chicago's Predictive Analytics Group

The overwhelmingly positive reception for GIS crime mapping in Chicago served as a catalyst for its further development, most notably incorporating temporal data to render cartographic representations of prospective crimes. Near the turn of the last decade, the CPD's Predictive Analytics Group synthesized crime prediction methods with GIS practices through an algorithm designed to deliver "specific and precise enforcement in a timely manner" (CPD 2011b). This did not establish conditions for more narrow applications of police force, however. On the contrary, it amplified rationalizations for policing entire racialized districts in a differential manner—this time, under the pretense of empirically rigorous spatiotemporal modeling. For one, the Predictive Analytics Group concentrated on finding spatiotemporal irregularities within official data sets but did not address the racialized irregularities implicit in the collection, recording, and dissemination of those data. Given city officials' enchantment with geovisualized crime data, the subsequent precrime maps based on these data did not only leave this racialized dimension embedded in official crime data intact but they also codified this dimension with a seal of scientific credence. Moreover, the CPD's Predictive Analytics Group correlated police data with other geocoded information and subsequently produced a range of geographic "indicators" of crime that were distinct to racialized districts. Both factors converged to further entrench the statistical criminalization of racialized police districts and legitimize the differential police control of them.

Validating CPD Data

From the start of Rahm Emanuel's (2011–current) administration, the mayor proved a vocal advocate of applying data analysis to government decision making to manage the burgeoning social disorders incurred or exacerbated by the Great Recession (UCCD 2013). Between 2008 and 2009, the monthly average unemployment rate in the Chicago metropolitan region increased from 6.1 percent to 9.2 percent (Bureau of Labor Statistics [BLS] 2016), and the rate for residents classified as black and Hispanic increased to 15.5 percent and 11.5 percent, respectively (compared to 3.0 percent for those classified as white), both almost 1 percent higher than national averages for both groups (U.S. Department of Labor 2010a, 2010b; BLS 2012). From 2007 to 2010 the percentage of unemployed people out of work for twenty-seven weeks or more rose from 22.6 percent to 48.9 percent in Illinois (Hoffman 2015). By 2012, almost 33 percent of residents classified as black lived below the poverty line, compared to 23.5 percent for those classified as Hispanic and 14.6 percent for those classified as white (U.S. Census 2012). That year, Illinois teen employment dropped to 27 percent, the lowest in the state's recorded history (Fogg, Harrington, and Khatiwada 2015), including a perplexing 92 percent of males age sixteen to nineteen categorized as black, and 80 percent of those categorized as Hispanic in Chicago city were jobless (Córdova, Wilson, and Morsey 2014).

Predictive crime mapping emerged as a central tool for mobilizing police to contain the disorders generated by these dislocations. On his inauguration, Emanuel appointed the city's first chief data officer (CDO), Brett Goldstein, a Big Data guru who served as a commander of the West Side's Harrison district, which at the time led all CPD districts in recorded arrests (CPD 2009). It was here that Goldstein contemplated how to "design a computer model that could replicate an officer's intuition," an impulse that propelled the department's predictive crime mapping system (Flock 2011). The CDO took the police department's crime data at face value and treated the data as if they were facts acquired through scientific methods despite the well-documented irregularities and inconsistencies in CPD data collection practices (Ramos 2013; ACLU 2016). Consequently, the Predictive Analytics Group built an entire computational structure around the subjective biases of patrol officers whose intuitions and instincts were cultivated in a regime designed to differentially monitor and control racialized surplus populations.

In 2009, Goldstein and Carnegie Mellon's Event and Pattern Detection Laboratory secured a grant from the NIJ to form the Predictive Analytics Group to combine data analytics with urban science. The group recognized three distinct objectives it wanted to achieve in analyzing the city's massive data sets: establish predictions of crime events up to one week in advance, establish spatiotemporal resolution at the scales of blocks and days, and develop the ability to predict emerging hot spots rather than simply just high-crime neighborhoods (Neill 2013). To do this, the group created CrimeScan software, which assimilates a sparse logistic regression model to machine learning to predict emerging hot spots of violent crime using multivariate data sets. In its early phase, the group focused on identifying statistical relationships within CPD data on 911 calls and shooting statistics. The team maintained it could extrapolate where and when future shootings would occur based on the assumption that time series in past data can be used to infer expected values in the immediate days afterward (Neill et al. 2005).

Employing this tautological logic, the Predictive Analytics Group expanded inputs beyond dispatch calls and shooting and homicide data. Specifically, it identified twelve indicators through spatial statistical analysis of crime in West Englewood, a neighborhood in which 95 percent of the residents were categorized as black (Nobles, Neill, and Flaxman 2014). Although the CPD will not reveal details about these findings, a former member of the Predictive Analytics Group explained:

> The most important leading indicator types seem to be certain sorts of minor crimes (for example, simple assaults predict aggravated assaults), gun-related 911 calls (shots fired, person with a gun, etc.), gang-related 911 calls (gang loitering, narcotics loitering, gang disturbances, etc.), and a few others (e.g., gambling). (Personal communication 2016)

The fundamental rule to emerge from the project was that a "significant cluster of any of the [leading indicators] are assumed more likely to have a spike in [violent crime] within the next 1 week" (Neill 2012, 7). The group thus sought to find correlations between crime events and less serious Part II offenses (Neill 2013; Goldstein 2015). Each additional statistical category shared an overwhelmingly positive correlation with racial classification, however. In 2009, 99 percent of gambling violations recorded by the CPD involved individuals classified as black, 93 percent of recorded narcotics violations involved individuals classified as black and Hispanic, 85 percent of instances of vandalism involved individuals classified as black and Hispanic, and 67 percent of simple assaults involved individuals classified as black (CPD 2010).

Moreover, in addition to identifying concentrations of Part II crimes as probable sites of future crime, the group employed kernel density–based prediction to locate and rank prospective hot spots according to their proximity to clusters of the ever-expanding catalog of leading indicators. By adding proximity into the equation, the circumference of prospective hot spots expanded, which in turn widened the proportion of racialized areas that were flagged as criminogenic. The multiplication of variables fed into the predictive mapping system therefore exemplified state cartographical practices' imbrication with "metaphors of reach, expansion and power" (Pickles 2004, 42), as it continuously reinforced and extended statistical justifications for the differential policing of racialized districts.

In the near future, members of the group expressed, predictions of crime will be scaled down to the hour of day. Indeed by its third iteration, the group accomplished its goals of achieving a temporal resolution down to the day, for up to one week (Neill 2012, 2013). By scaling predictions down from twenty-four hours to one hour, though, the number of prospective crime events generated by the Predictive Analytics

Group invariably multiplies. "More [temporal] precision in our model," explained a one-time member of the GIS team, "gives [police] more targets to deal with." Given the racialized composition of the crime data fed into the model, gradating the timescales increases the number of prospective hot spots located primarily in racialized police districts. As Valverde (2014) noted, the temporal logics of crime prevention are inextricably tied to the spaces over which agents of crime prevention exercise control. This is evident in precrime mapping, as more temporal precision translates into more targets of preemptive control, which ultimately legitimizes the more widespread and indiscriminate patrolling of racialized districts.

To be certain, the group and other CPD officials discount any racial patterns observed in predictive mapping outputs as coincidental. Analysts and police personnel deflect charges of racism on grounds that algorithms are not fed protected categories such as race or neighborhood and as predictive analysis is a quantitative pursuit. In fact, quantitative analysis is construed as diametrically opposed to racial bias. "This program," one of the group's founders asserted, "had absolutely nothing to do with race ... but [rather] multi-variable equations" (Tett 2014). "Actually," a commanding officer explained, "there's no information about race, gender. Nothing about even geography, neighborhood, nothing about that goes into the predictive model. So there's nothing about that at all in the model. It's all objective elements of a criminal history" (Interview 2015). But insofar as the crime data are always already racially skewed, the predictive mappings cannot help but overrepresent racialized districts, irrespective of the algorithms they run.

Microgeographic Indicators of Crime

In addition to finding spatiotemporal anomalies within official crime data sets, the group sought to find more correlations between crime events and microgeographic conditions in neighborhoods with high crime indexes. A one-time director of the group explained that maximizing the accuracy of predictions required spatial information that is "as granular as possible, typically at the census tract level" (Interview 2015). In achieving higher levels of accuracy, the Predictive Analytics Group began using CrimeScan to test for spatialized indicators of future crime using the city's Data Portal, one of the largest open databanks in the country, consisting of more than 900 data sets on municipal departments, faculties, and services. Inasmuch as the crime data sets directed the group to find spatialized indicators exclusively in racialized police districts, however, each indicator ended up being a microgeographic phenomenon typical to districts categorized as majority black and Hispanic.

In looking for correlations between crime and spatialized indicators, the Predictive Analytics Group sought to pinpoint "micro-geographic targets" at the subblock scale and gather more detailed information about these areas than census tract data provide. To do so, it adopted an open source database that allows officials to create overlay maps of neighborhoods that include "unstructured data" such as the area's number of liquor licenses, abandoned buildings, or complaints about garbage disposal and road conditions (Schectman 2012). Members of the group noted:

> Part of what we do is both identifying leading indicators of, let's say, violent crime and modeling the impact of those leading indicators at a very fine temporal and spatial resolution. So the idea is that we may actually be able to more precisely answer questions like: what happens when you demolish some abandoned buildings? One of these where we can really kind of draw hopefully not just predictive, but eventually causal connections between things like the whole broken windows policing thing, [for instance] the vacant buildings, the graffiti. (Interview 2015)

> In reality what we're doing is a couple things. We're looking at geographic areas with abnormal crime, but we're also learning more and more about the conditions in these areas. And then we can say, "OK, given historical data and our analysis, where and when will future crime happen in these areas with more and more preciseness." (Interview 2015)

Several aspects of high-crime areas' built environments were articulated as criminogenic indicators through this approach. When discussing what type of unstructured data were layered in predictive crime mapping techniques, the group's members cited dilapidated infrastructure and unkempt conditions (Goldstein 2015), residential complaints (Sverdlik 2012), quality of life conditions (Schectman 2012), and decrepit facilities (Neill 2013). Some key advancements in predictive analysis and mapping identified by the team included newfound abilities in "mapping out the number of liquor permits for a neighborhood, along with the amount of nearby abandoned buildings. [We also map] trending concerns for the area, like broken lights or stolen garbage cans" (Schectman 2012).

As geographies of dilapidation and disrepair are unmistakably racialized, though, these geographic indicators further legitimated the differential policing of racialized places. This is particularly salient when it comes to abandoned buildings. By the end of 2012, the rate of long-term (at least twenty-four months) residential housing vacancies per residential address was exponentially higher in Black Belt neighborhoods when compared to the rest of Chicago. West Englewood's rate was 155 percent higher than the city average (2.86 percent), Woodlawn's rate was 180 percent higher, Washington Park's was 246 percent higher, Englewood's was 256 percent higher, and Riverdale's was an astonishing 711 percent higher than the city average (Institute for Housing Studies 2013). To compound matters, community areas with exorbitant residential vacancies are targeted for disinvestments in an array of public services including garbage disposal and road repair (Chicago Area Fair Housing Alliance 2013). The physical disorder stemming from entanglements of abandonment and disinvestment is particularly acute across South Side neighborhoods, where more than 50 percent of residents reported graffiti and trash as a problem in 2010 (compared to city averages of 21 percent and 27 percent, respectively; Roman and Knight 2010).

The compulsion with finding correlations between crime events and increasingly microscalar phenomena eventually led the group to designate individuals as geocodable sites of predictive crime analysis. As crime offenders and victims are represented as "points operating over time within a polygon. [So] they can also be portrayed as predictable events, once mathematics and computation are effectively applied" (Goldstein 2015, 8). As such, microgeographies of formerly convicted individuals emerged as spatial indicators of future crime, as the Predictive Analytics Group viewed prior criminal offense as the most powerful predictive variable of prospective crime events. Because individuals bureaucratically categorized as "black" accounted for about 72 percent of all CPD arrests in 2009 (CPD 2010), the search for probabilities of future criminal activity invariably gravitates toward Black Belt areas, which in turn provides a quantized rationale for excessively monitoring enclaves of racialized subjects.

By adding extra layers of geographic indicators of crime onto precrime maps, the group supplied another ostensibly scientific pretext for enhancing police controls in racialized districts. This proliferation of microgeographic correlates of crime events reflects state GIS practices' penchant to increase surveillance and social control (Sheppard 1995). Inasmuch as the group recognized a greater number of physical disorders as being linked to crime, it legitimized increased police monitoring and intervention in areas where vacant buildings, abandoned lots, graffiti, and other physical disorders are clustered. In sum, the group's reliance on CPD crime data validated the hyperscrutinization of majority black and latinx districts, and the group's penchant for finding an increasing number of correlations between crime and geographic phenomena ensured that the surface area within these districts that is recognized as criminogenic expanded accordingly. These factors combined to leverage spatial statistical analysis and geovisualization in service of racialized policing and legitimate it on scientific grounds. The following section chronicles how this logic is put into action.

Predictive Policing in Practice

Much like the CPD's operations using ICAM in the 1990s, its initiatives using precrime maps have also involved putting GIS in the service of legitimizing and organizing police operations deployed in majority black and latinx districts. Three recent police initiatives exemplify this: strategic subjects list, hot mapping, and custom notifications. Although modes of racialized police profiling are nothing new, predictive analytics supplied police with a new rationale for expanding racial profiling and intervening in majority black and latinx districts in new ways.

Chicago's first foray into predictive policing commenced when the CPD, along with the Illinois Institute of Technology and NIJ funding, began its strategic subjects list (SSL) pilot. SSL was meant to use police resources in a more economical manner by focusing them on at-risk subjects rather than known offenders. To do this, the team devised an algorithm that uses data inputs including narcotic arrests, gang affiliation, and age at the time of most recent arrest. It also used social network analysis to estimate a subject's relative risk of engaging in future violent crime according to her or his links to homicide victims (Saunders, Hunt, and Hollywood 2016).

Although the algorithms that generate the SSL are sealed from the public, each input that has been publicly acknowledged holds an exceptionally strong correlation to race. In 2010, arrestees categorized as black or Hispanic accounted for approximately 93 percent of all narcotics arrests (CPD 2011a). About 96 percent of all arrestees for nonnegligent manslaughters were categorized as black or latinx (CPD 2011a). That year, 93 percent of all recorded murders occurred in CPD districts classified as majority black or latinx (CPD 2011a). Victimization data show similar racialized compositions. In 2011, 75 percent of murder victims recorded by the police were categorized as black, 19 percent as latinx, and almost 5 percent as white (CPD 2012).

Moreover, the SSL has shown a remarkable penchant for increasing the amount of individuals it recognizes as risky. Originally, the predictive analysts ran network analyses on sixty gangs and 600 factions to predict potential acts of retaliatory violence in the aftermath of homicides (Joh 2016). In 2013, the department's Deployment Operation Center began generating trimonthly lists of the 500 highest risk individuals in the city; that is, each of the twenty-five districts' twenty most at-risk subjects. Toward the end of 2013, the department created a separate list of the city's 426 riskiest subjects to circulate to district commanders (Saunders, Hunt, and Hollywood 2016). By the end of the program's first two years, the total number of subjects identified as at risk has increased by more than 200 percent, totaling more than 1,400 names (Robinson 2016).

The CPD acted on the expansive SSL through "call-ins." The method originally involved joint efforts among police, federal, and county authorities and the Illinois Department of Corrections to identify and round up members of gangs to warn them that they would be targeted in the event of a spike in violent crime. In 2015, the department began calling in groups of high-risk subjects identified on the SSL who lived in close proximity to one another. The centerpiece of the initiative involved rounding up targeted subjects and collectively informing them that they would be prime suspects should a sudden increase in index crimes occur in their vicinity. Call-ins thus functioned as unequivocal admissions on behalf of the police that certain individuals, geographically concentrated in certain places, were permanently subjected to differential police scrutiny.

Keenly aware of the program's potential controversy, CPD personnel insisted that it was in no way related to racial profiling but instead relied on calculations of objective crime data:

> [The predictive model] does things a human being could do if they had lots of time. . . . [It is as if to say], "I'm going to sit down and look through 4,000 arrestees and now look at all their criminal histories and look at how these different factors might weigh in on developing a risk score for them." It automates that and improves the efficiency and actually improves the objectivity because, again, it just measures very objective elements of people's criminal arrest histories. (Interview 2015)

> [The model analyzes] type of arrests, trend line in arrest activity increasing or decreasing, age at most recent arrest—the lower the age the higher the correlation/the higher the risk, things like are there weapons arrests, was the person victimized in a shooting themselves, which tends to increase their future risk as you would imagine. (Interview 2016)

> [It is] similar manner to how the medical field has identified statistically that smoking is a risk factor for lung cancer. Of course, everybody who smokes doesn't get lung cancer, but it demonstrably increases the risk dramatically. The same is true of violent crime. (Cantuó 2014)

Such statements illuminate how the trenchantly racialized dimension of the SSL was disregarded on account of CPD data sets, even though the data sets were not constructed using scientific methods.

In addition to the SSL, the department devised several "hot mapping" tactics, which employed the CPD's Gang Violence Reduction Strategy in areas where high-risk subjects were spatially clustered (Saunders, Hunt, and Hollywood 2016). The key component of the strategy pivoted around "focused deterrence" and apprehension programs for identifying and intercepting subjects with prior records who are deemed likely to violate mandatory curfew hours, residency requirements, or prohibitions against associating with gang members. Additional practices included tactical saturation of gang territories, targeted vehicle enforcement of motorists who violate quality of life ordinances, and the permanent patrolling of problematic beats (see Escalante 2015). The hot mapping initiative thus added another layer of "homogenous areas of commonality" (Goldstein 2015, 8) marked for differential control, this time based on concentrations of potential parole violators.

The third program rolled out in predictive policing experiments was the custom notifications pilot. This initiative was developed in tandem with John Jay College's Violence Reduction Initiative and involved CPD officers making direct contact with high-risk individuals on the Crime Prevention and Information Center's "heat list" at their place of residence. These interactions were meant to inform heat-listed subjects of the arrest, prosecution, and sentencing consequences they might face "should they engage in criminal conduct" (McCarthy 2013). According to the program, district commanders and officers were to identify the living quarters of subjects on the heat list, conduct home visitations to deliver custom notification letters, and inform subjects or cohabitators that law enforcement actions in their areas would not be random but instead based on the statistical correlations discovered in the predictive model. Like the hot mapping tactics, custom notifications were defended on the grounds that they are based on irrefutable, objective calculations (Papachristos 2016).

To be sure, the custom notification initiative also involved social service and community partners when interacting with heat-listed subjects. Home visitations included police explaining the content of warning letters and providing at-risk subjects with information about various social agencies and job and extracurricular programs conducive to crime prevention. The point, though, is that the initiative nevertheless increased police-to-civilian interaction, expanded categories of subjects marked for differential monitoring, and added home residences into the ambit of predictive policing. In fact, the development of the heat list was viewed as an advancement as it pinpointed "high-risk individuals [who] were not necessarily under official criminal justice supervision nor were they identified through intelligence to be particularly criminally active" (Saunders, Hunt, and Hollywood 2016, 349). Moreover, the initiative's racial dimension was clear. By the end of the pilot, each recorded notification was enacted in majority black or latinx districts on the South and West Sides (LD Consulting 2014).

Proclamations of unbiased and objectively precise policing notwithstanding, the CPD's own data suggest that the race–policing nexus has remained perfectly intact since its turn to precrime mapping; racialized policing simply has obtained a new, ostensibly scientific justification. Indeed, racial disparities in police–civilian encounters in Chicago—which U.S. Census data breaks down as 33 percent black, 31 percent white, and 29 percent latinx—are remarkably consistent across types of interactions. Roughly three fourths of recorded CPD–civilian engagements involve civilians classified as black. Circa the Predictive Analytics Group's inception to 2015, 74 percent of civilians shot by CPD officers were classified as black, 14 percent were latinx, and 8 percent were white (PATF 2016). Black subjects comprised about two thirds of all fatal shootings, and 60 percent of shootings occurred in Black Belt districts (Schroedter 2015). Police tasers were used on black subjects 76 percent of the time, on latinx subjects 13 percent of the time, and on white subjects 8 percent of the time (Schroedter 2015). In 2014, quarterly data suggested that some 254,499 people were stopped and questioned or frisked due to officer suspicion—a rate more than four times that of New York City once adjusted for population (ACLU 2015). Of those stopped, 72 percent were classified as black, 17 percent as latinx, and 9 percent as white (ACLU 2015).

Conclusion and Discussion

Although predictive policing has been met with considerable criticism and is being reevaluated by city authorities, it nonetheless sheds light on connections between geographic information production and the differential control of racialized populations and places. In specific, the Chicago case illustrates that predictive crime mapping does not incur more precise applications of police force but rather legitimizes the widespread criminalization of racialized districts. Precrime maps lend a seal of scientific approval to official crime data sets that were not compiled through scientific method for one, and they rearticulate an ever-increasing range of geographic conditions typical to racialized districts as criminogenic for another. Precrime maps garb the epistemologies of racialized policing in a scientific veneer, by mobilizing the language of spatial statistical analysis and data analytics to bolster city officials' rationale for using differential police surveillance and control in Black Belt and latinx districts.

The implications of these findings for critical geography are twofold. First, the analysis contributes to geographic encounters with police, race, and neoliberal urbanization by showing the central role that geographic information production plays in rendering communities of economically redundant and racialized labor fractions as sites of intensified social control. Not only does racialized policing proceed through the mental maps that officers construct to rationalize differential territorial practices (Herbert 1996), but it also spreads through the bureaucratically produced geographic information bits that codetermine the scope and intensity of policing in racialized districts. Second, my analysis advances knowledge in critical GIS literature by elucidating the role that GIS has in constituting and controlling racialized subjects and spaces. Specifically, the article casts into relief the way in which the GIS-based precrime maps contribute to reducing racialized problem populations and the social disorders that afflict them to objects of intensified police surveillance and control.

Moreover, the analysis suggests that the pervasiveness of GIS-based policing practices spreads alongside the growth of racialized problem populations. That societal conditions shape the development and utilization of GIS is well established (Sheppard 1995). Furthermore, geographers have chronicled the "power of GIS to discipline, to produce geography and other sites in its own image" (St. Martin and Wing 2007, 242). Examination of predictive crime mapping thus provides deeper insights into the concrete social function of policing in neoliberalizing cities. In particular, GIS furnishes police with a serviceable tool to identify and intercept problematic persons dislodged by deindustrialization, labor market bifurcation, and recent rounds of urban redevelopment with greater efficiency.

In sum, the analysis uncovers policing as a quintessentially geographical mechanism of population management, which operates in conformity with the political economic system. Through this analysis, I situate racialized policing as a problematic located squarely within the provenance of critical geography, not only the more narrowly focused fields of police studies and criminology. I show how racialized subjects and spaces are (re)produced in part through place-specific modes of police control that necessitate the constant production of geographic information. Although GIScientists, crime experts, and police might not undertake the development and deployment of GIS crime maps with intentions of exacerbating sociospatial differentiation, the effects of relying on official data are inextricably linked to expanded monitoring and patrolling of racialized districts. Policing technologies and practices, which are developed and deployed according to logics of capital accumulation within racially stratified, neoliberalizing cities, cannot fail but reinscribe place-based racial differentiation.

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Notes

1. In 2006, the Memphis Police Department teamed with University of Memphis criminologists to create its Blue CRUSH system, which uses IBM predictive analytics to narrow patrol areas to a few square blocks of prospective crime (Vlahos 2012). That year, the Los Angeles Police Department began working with UCLA researchers to develop a model that simulates future crime diffusion and dissolution patterns (Pittman 2010). The Santa Cruz Police Department uses a mapping system that shows the probability of property crimes in 500 × 500 foot areas by the hour. The software uses an algorithm to predict the spread of property crimes based on a method used by seismologists to forecast earthquake aftershocks, and was credited for bringing property and violent crime to their lowest levels since 1973 (Thompson 2011).
2. Herbert's (1996, 2005; Herbert and Brown 2006) work, which is examined later, provides a notable exception.
3. This argument is derived from Turk (1969).
4. These materials were located using search phrases including "predictive analytics group," "CrimeScan," "geographic information systems," and "CLEARmap," which stands for Citizens Law Enforcement and Reporting map. It is the CPD's current GIS crime mapping application.
5. Manning's (2011) book, *The Technology of Policing*, explores the impact (or lack thereof) that GIS crime analysis and mapping has on the internal, day-to-day operations of police. This article, by contrast, explores how these technologies are used by police officials to legitimize such operations.
6. Data are from 1990 (U.S. Census 2000).
7. Black Belt neighborhoods are at least 80 percent black community areas, including West Garfield Park, East Garfield Park, North Lawndale, Near West Side, Near South Side, Douglas, Oakland, Grand Boulevard, Washington Park, and Englewood.
8. Statistics were not kept for latinx inmates in 1995.

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