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METHODS, TOOLS, DATA, AND SOFTWARE

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A data framework for assessing social inequality and equity in multi-sector social, ecological, infrastructural urban systems

Focus on fine-spatial scales

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Abstract

Cities are increasingly advancing multiple societal goals related to environmental sustainability, health, well-being, and equity. However, there are few comprehensive data sets that address social inequality and equity across multiple infrastructure sectors, determinants, and outcomes, particularly at fine intra-urban spatial scales. This paper: (1) Offers an overarching conceptualization of inequality and equity in multi-sector urban systems; (2) Introduces a broad data framework to assess inequality and equity across social (*S*), ecological (*E*), infrastructural (*I*), and urban (*U*) form determinants (*SEIU*) and environment (*E*), health (*H*), well-being (*W*), and economy and security (*E*) outcomes (*EHWE*), identifying a universe of >110 SEIU–EHWE data layers (variables) of interest; (3) Provides an illustrative data case study of a US city that synthesizes publicly available sources of the associated SEIU–EHWE data attributes, noting their availability/gaps at fine spatial scales, important to inform social inequality; (4) Discusses analytic methods to quantify inequality and spatial correlates across SEIU determinants and EHWE outcomes; and, (5) Demonstrates several use-cases of the data framework and companion analytic methods through real-world applied case studies that inform equity planning in applications ranging from energy sector investments to air pollution and health. The US data case study reveals data availability (covering 41 of the 113 data layers) as well as major gaps associated with EHWE outcomes at fine spatial scales, while the application examples demonstrate practical use. Overall, the SEIU–EHWE data framework provides an anchor for systematically gathering, analyzing, and informing multiple dimensions of inequality and equity in sustainable urban systems.

KEYWORDS
data framework, industrial ecology, social ecological infrastructural urban systems, social equity, spatial inequality, sustainable urban systems

1 | INTRODUCTION

Cities are increasingly engaged in planning efforts to advance multiple societal goals related to environmental sustainability, health, well-being, and equity. For example, New York City's goals span the economy, social justice, sustainability, and resilience (City of New York, 2015, 2019). Other examples from the United States include Denver's climate action plan emphasizing equity goals (DPHE, 2018) and Portland's racial equity plans across city bureaus (City of Portland, n.d.). These city-level efforts are consistent with the focus on reducing inequality in the United Nations (UN) Sustainable Development Goals (SDGs) (UN, 2015) and New Urban Agenda (UN Habitat, 2017). SDG 11 focuses on developing "sustainable cities and communities," with sub-targets focusing on inclusive development. Moreover, SDG 11 is linked to virtually all others—including health and well-being (SDG 3), reducing inequality (SDG 10), achieving zero hunger (SDG 2), reducing poverty (SDG 1), and enhancing access to clean water (SDG 6) and clean energy (SDG 7). Practically speaking, cities are grappling with several challenges related to social inequality—including food insecurity, lack of access to housing and sanitation, unequal access to transportation, high energy cost burden for low-income residents, and unequal exposure to health risks ranging from air pollution to climate extremes—all of which are expected to be exacerbated with climate change, migration, and rapid urbanization.

At the global and the urban level, physical and social provisioning systems are foundational to the SDGs. At the global scale, cross-national analysis (O'Neill et al., 2018) reveals the foundational role of physical and social provisioning systems in shaping inequality in access to basic services, income, life span, and life satisfaction, among others, alongside planetary boundaries. In the context of urban systems, Ramaswami et al. (2016) highlight the importance of seven provisioning systems (or "sectors")—energy, buildings, mobility, green space, water, waste, and food systems—impacting human health and the planet from local-to-global scales. For example, the energy sector alone accounts for more than 70% of global greenhouse gas (GHG) emissions when energy imports to cities are considered (Seto et al., 2014), while water supply to 50 of the world's largest cities draws upon more than 40% of the world's watersheds (McDonald et al., 2014). Inadequate access to these provisioning systems, pollution arising from these systems, and disruptions due to extreme climate events, together contribute to the vast majority of noncommunicable disease burden globally, resulting in an estimated 19.5 million premature deaths annually (Lim et al., 2012; Ramaswami et al., 2016). Within cities, disparities in objective measures of health outcomes can be very high, for example, lifespan disparities of 25 years in New Orleans and 13 years in Atlanta, between proximal neighborhoods (VCU, 2016). In addition to objective measures of health, subjective well-being—defined as how people think and feel about their lives (CDC, n.d.)—is now regularly measured via national and cross-national surveys such as the Gallup World Poll (Helliwell et al., 2020) or the United Kingdom's well-being survey (ONS, 2020), and shows well-being disparities by age, income, and other complex social, environmental, and infrastructural attributes. These studies begin to highlight that inequality is relevant across both determinants and outcomes, and they point to ways in which unpacking nexus relationships among infrastructure, health, well-being, and the environment can yield new science to inform equity policies in cities (Ramaswami, 2020).

While there is a growing body of work on these topics, multiple dimensions of inequality have not yet been comprehensively studied or characterized at intra-urban scales across all key provisioning sectors and multiple sustainability outcomes. Various disciplines—including environmental science, public affairs, economics, urban planning, public health, and sustainability sciences—have studied intra-urban inequalities, focusing on particular sectors or outcomes of interest. Our paper contributes by defining inequality and equity in the emerging field of sustainable urban systems science (ACERE, 2018) and developing an urban systems-based data framework that addresses multiple sectors, determinants, and outcomes.

Data are particularly needed at *fine intra-urban spatial scales* where social disparities manifest spatially in cities, e.g., by neighborhood income, race/ethnicity. However, gathering data at these fine spatial scales presents challenges (NASEM, 2019). Scientists and practitioners are grappling with what data to gather, and how, when studying equity across interacting determinants and outcomes in cities. Thus, the overarching goal of this paper is to develop data capacity to link multiple infrastructure sectors, determinants, and outcomes for multi-dimensional analysis of intra-urban inequality.

Specifically, the five objectives of our paper are to:

1. Review inequality and equity in multi-sector urban systems, drawing upon concepts from multiple disciplines (Section 2).
2. Introduce a broad data framework to evaluate inequality and equity across both determinants and outcomes in multi-sector urban systems (Section 3).
3. Provide an illustrative review of publicly available data and to identify data gaps at finer intra-urban spatial scales (Section 4).
4. Discuss methods of analysis of finer intra-urban spatial-scale data for inequality and equity across determinants and outcomes (Section 5).
5. Demonstrate example applications of such analysis and to discuss its potential to inform equity planning in cities (Section 6).

We illustrate our data framework through case studies focusing on US cities. The framework is widely applicable to cities globally, given the universality of determinants and outcomes.

Our paper focuses on fine-scale *spatial data* to assess social inequality within cities. Addressing fine-scale *temporal* data is beyond the scope of this paper, given our focus on intra-urban socio-spatial inequality, and because the relevant temporal scale of data varies by topic of interest; for example, access to housing may be assessed using monthly or annual surveys, whereas heat exposure assessment requires hourly data.

2 | A REVIEW OF INEQUALITY AND EQUITY IN SUSTAINABLE URBAN SYSTEMS

Sustainable urban systems science addresses multi-scale interactions among social systems, natural systems, and multiple key provisioning sectors in cities, as they shape the various outcomes of interest in society, such as health, well-being, environmental sustainability, and equity (ACERE, 2018; ISIE, 2021; Ramaswami, 2020; Ramaswami et al., 2012). The study of sustainable urban systems is interdisciplinary and encompasses fields of economics, public policy, urban planning, infrastructure engineering, industrial ecology, environmental science, and public health (Ramaswami et al., 2012), as well as complexity science (Batty, 2009). Each of these disciplines has studied urban social inequality in different contexts. For example, urban planners examine inequalities in access to key provisioning sectors, often within single sectors, such as walkable neighborhoods (Su et al., 2017), nutritious food (Lowery et al., 2016), and green space (Wüstemann et al., 2017). Emerging studies are addressing inequalities across multiple sectors in different cities (Brelsford et al., 2017), with industrial ecologists combining inequalities in access and consumption (e.g., of energy; Nagpure et al., 2018), and linking these with GHG emissions (Goldstein et al., 2020). Environmental justice research, often focusing on distributions of burdens, also called maldistributions (Schlosberg, 2007), investigates inequalities in various exposures and risks, such as air pollution (Bravo et al., 2016), noise (Verbeek, 2019), heat risk (Mitchell & Chakraborty, 2015), and flood risk (Walker & Burningham, 2011). On the other hand, economists and public affairs scholars often study inequality in income and in the distributions of public goods, such as investments in education (Haddad & Nedović-Budić, 2006) and renewable energy (Chan et al., 2017).

Health outcome disparities are regularly studied in public health in the context of social and environmental determinants of health (Gee & Payne-Sturges, 2004; Singh et al., 2017; WHO, 2008), but are not often linked with broader environmental sustainability outcomes, such as GHG emissions. Such linkages of human health and environmental sustainability outcomes are emerging in sustainability science (Guo et al., 2020; Ramaswami et al., 2017) and under the banner of planetary health (Horton et al., 2014), but are largely implemented at national or global scales. There is interest as well in the broader concept of well-being, beyond disease burden, incorporating concepts of sufficiency and happiness (Helliwell et al., 2012; Steinberger & Roberts, 2010), with the broadest conceptualization of sustainability emerging as advancing well-being for all within planetary boundaries (O'Neill et al., 2018). Key physical and social provisioning systems (or sectors) have been articulated as central to address both human well-being and planetary boundaries (O'Neill et al., 2018; Ramaswami, 2020).

Our data framework addresses this broad conceptualization of urban sustainability, wherein inequality is explored across sectors, determinants, and outcomes. We clarify that inequality and equity are related, but not one and the same.

Inequality measures the degree of difference or disparity in the distribution of various attributes of urban systems (e.g., income, access to social and physical provisioning systems, exposures to environmental risks) across populations or among social groups. Inequality within cities often shows strong spatial patterns of social stratification across neighborhoods by income/class, and along lines of race, ethnicity, and migrant status (Kilroy, 2009), which can manifest as consequential neighborhood effects (Sampson et al., 2002).

We define *equity* as addressing fairness in the societal distribution of burdens and benefits, across determinants and outcomes, with the goal of reducing disparities for the most disadvantaged, by, for example, race/ethnicity, income/class, gender identity, migrant status, or age. This focus of equity on reducing disparities for the most disadvantaged draws theoretically from Rawls' theories of distributive justice, Sen's human capabilities approach, and scholarship defining equity in public health (Braveman, 2006). The focus on both determinants and outcomes is important to address causes of inequality rather than only the final outcomes (Schlosberg, 2007).

Our data framework addresses *distributional equity* (i.e., equity in the societal distribution of burdens and benefits) and does not directly address *procedural equity*, which considers the extent to which communities most negatively impacted by inequitable distributions of burdens/benefits are represented in, and are able to influence, plan-making and decision-making processes (Sovacool et al., 2017). *Social justice* includes both distributive and procedural equity and is often used interchangeably with *social equity* (Braveman, 2006; Burton, 2001).

3 | DATA FRAMEWORK FOR ASSESSING INTRA-URBAN INEQUALITY AND EQUITY

Figure 1 presents an overarching *SEIU–EHWE data framework* for bringing together diverse data to comprehensively assess intra-urban distributional inequality and equity. The SEIU–EHWE data framework draws upon a multi-sector transboundary social–ecological–infrastructural systems framework (Ramaswami et al., 2012), considering environmental and health outcomes associated with key physical provisioning systems. That original articulation has evolved to now include physical, cyber, and social provisioning systems, encompassing multiple broad societal outcomes,

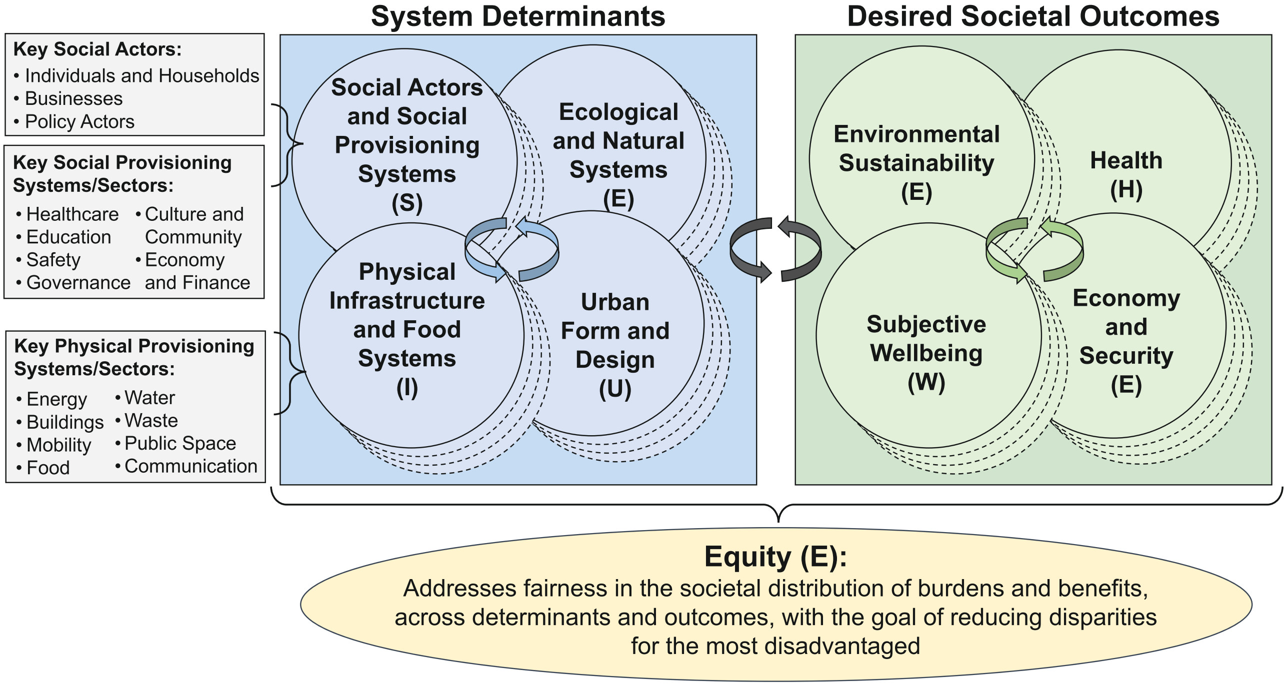

FIGURE 1 Schematic representation of the SEIU–EHWE data framework depicting complex interactions among desired societal outcomes (right panel; organized into four categories: environmental sustainability, health, subjective well-being, and economy and security ["EHWE outcomes"]) and determinants of desired societal outcomes (left panel: organized into four categories: social actors and social provisioning systems, ecological and natural systems, physical infrastructure and food systems, and urban form and design ["SEIU determinants"]). Each of the determinant and outcome categories contains multiple sub-categories and layers (as indicated by the ellipses with dashed lines). Arrows indicate complex interactions among system determinants and desired societal outcomes. Key physical and social provisioning systems (or sectors), as well as key categories of social actors, are listed as system determinants. Equity (bottom panel) is defined as in Section 2 and assessed across both determinants and outcomes

spanning environment, health, well-being, and economy and security, as well as questions of distributional equity across these outcomes (Ramaswami, 2020; Ramaswami et al., 2016). These advances were co-developed with cities in a series of workshops of the Sustainable Healthy Cities Network (SHCN, 2018) and are consistent with international policy and sustainability frameworks (GPSC, 2018; UN Habitat, 2017) and sustainability sciences' literatures (O'Neill et al., 2018). Recent work articulates a central focus on distributional equity as sitting at the heart of the urban infrastructure—sustainability—well-being nexus (Ramaswami, 2020). Thus, our framework explicitly conceptualizes equity across multiple interacting sectors, determinants, and outcomes.

Specifically, our data framework is structured around categories of *system determinants* (*SEIU*) and *desired societal outcomes* (*EHWE*) (Figure 1). The SEIU–EHWE data categories are further structured into sub-categories and layers for organizing data attributes (see Figure S1 in the Supporting Information), using nomenclature from geographic information systems (Fang et al., 2014). The data layer can be thought of as the general variable of interest that may be used in models, while the data attribute refers to specific ways of representing or measuring that variable. For example, for the "income" data layer, associated data attributes would include "median household income" and "per capita income."

We delineated data categories, data sub-categories, and data layers (Table 1) based on a review of literature at the nexus of urban inequality, health, and sustainability, drawing on research papers and policy documents (Table 2). In total, we delineated 8 data categories, 28 data sub-categories, and 113 data layers for categorizing data attributes of interest (Table 1). As illustrated in Table 2, the SEIU–EHWE data framework categories and sub-categories provide broad coverage of themes cited in related literature. In the next section, we further describe the SEIU–EHWE categories, providing examples of the data layers and attributes within each sub-category. The data layers and associated data attributes may include both *objective* measures, such as of life span to representing health, as well as *subjective* measures, such as self-reported scores representing well-being, derived from surveys.

3.1 | Categories of system determinants

The four categories of system determinants are: social actors and social provisioning systems (or, *S*, for short), ecological and natural systems (*E*), physical infrastructure and food systems (*I*), and urban form and design (*U*), collectively termed *SEIU determinants*, and defined as follows:

TABLE 1 Categories, sub-categories, and layers within the SEIU–EHWE data framework

	Categories	Sub-categories	Layers	Primary reference
Determinants	Social actors and social provisioning systems (S)	Basic demographic	Population, race and ethnicity, education, language, age, gender, nativity	Standard from census
		Basic economic	Income and wealth, poverty, homeownership, employment, jobs, businesses	Standard from census
		Social provisioning systems	Healthcare, education and training, safety and emergency, culture and community, governance, economy and finance (e.g., availability of credit, capital, and banking)	Many; see Table 2
		Beliefs and attitudes	Political attitudes, environmental attitudes, health attitudes	Not standardized
		Social cohesion and engagement; community efficacy	Democratic participation, community participation, residential stability/turnover, perceptions of safety/belonging/community	Dempsey et al., 2011; Sampson, 2017
		Equity-related policies and investments	Program investments (e.g., in energy efficiency; supplemental nutrition programs)	Not systematically covered previously across sectors
		Local government policy capacity	Metrics are in research stage for urban scale (standard measures available for nations)	Hsu, 2015; Wu et al., 2015
	Ecological and natural systems (E)	Water, soil, and ecological systems	Soil, land, ecosystems, water, vegetation	Standard from USGS, USDA
		Weather and climate	Temperature, precipitation, wind, climate	Standard from NOAA
		Natural hazards	Floods, landslides, extreme temperature, storms, sea-level rise	Standard from NOAA
	Physical infrastructure and food systems (I)	Access	Energy, buildings, mobility, public space, water, waste, food, communication	Sector-specific sources (e.g., Bhatia & Angelou, 2015 for energy access)
		Consumption	Energy, buildings, mobility, public space, water, waste, food, communication	Consumer expenditure surveys

(Continues)

TABLE 1 (Continued)

	Categories	Sub-categories	Layers	Primary reference
		Distribution and production	Energy, buildings, mobility, public space, water, waste, food, communication	Sector-specific sources for production data (e.g., USGS, eGrid, USDA); Distribution networks often proprietary or protected data sources
		Disruption and failure	Energy, buildings, mobility, public space, water, waste, food, communication	Not systematically covered previously across sectors
	Urban form and design (U)	Density	Population density, employment density, built environment density	Cervero & Kockelman, 1997; Clifton et al., 2008
		Land use	Land use, zoning	
		Spatial design	Building design features, transportation network design features, jobs–housing balance, distance from central business district	
Outcomes	Environmental sustainability (E)	Local in-boundary pollution and degradation	Air quality, greenhouse gas emissions, water quality, heat islands, noise pollution, contaminated sites, solid waste	EPA
		Transboundary footprints	Materials, water, land, greenhouse gases	Chen et al., 2019; Chavez & Ramaswami, 2011
	Health (H)	Objective health outcomes	Morbidity (communicable conditions), morbidity (noncommunicable conditions), mortality, life expectancy and lost life years	CDC; GBD, 2017
		Health risks	Exposure to environmental pollution, vulnerability to natural hazards, safety	Small area health risk assessment (e.g., Dwyer-Lindgren et al., 2017); social vulnerability (e.g., Cutter et al., 2003)

(Continues)

TABLE 1 (Continued)

	Categories	Sub-categories	Layers	Primary reference
		Health behaviors	Physical activity, nutrition and diet, sleep, smoking and alcohol use, preventative healthcare	CDC
	Subjective well-being (W)	Emotional well-being	Standardized surveys, such the Gallup Happiness Survey, the UK's Office of National Statistics measures of individual and population well-being, and the American Community Survey, measure all three aspects of subjective well-being (i.e., emotional well-being, cognitive or evaluative well-being, and life purpose)	Helliwell et al., 2012; UK ONS, 2020
		Cognitive or evaluative well-being		
		Life purpose		
	Economy and security (E)	Economic measures	No consistent metrics have emerged for security, other than GDP per capita and percentage of population with resources less than basic needs; these are covered in the social (S) category above. Surveys of security overlap with well-being surveys. Resilience is defined as both a latent feature of a system as well as an outcome; social–ecological resilience outcomes at the community level are also increasingly measured using surveys, overlapping with well-being surveys	Our review of literature
		Basic access		
		Resilience		

TABLE 2 Synthesis review of frameworks, planning reports, and data tools regarding urban sustainability and/or equity, illustrating variable coverage[a] of SEIU determinants and EHWE outcomes

			Reviews and frameworks								*Planning reports*				*Data tools*		
			Dempsey et al., 2011	GPSC, 2018	ISO, 2018	Lynch et al., 2011	NASEM, 2016	O'Neill et al., 2018	Science for environment policy, 2015	UN DESA, 2007	City of New York, 2011	Coalition for a Livable Future, 2007	Mile High Connects, 2011	Partnership for Southern Equity, 2017	CA OEHHA, 2018	US EPA, 2019	PolicyLink & USC, 2020
Determinants	**Social actors and social provisioning systems**	Basic demographic	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		Basic economic	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		Social provisioning systems	X	X	X	X	X	X	X	X	X	X	X	X			X
		Beliefs and attitudes									X	X					
		Social cohesion and engagement; community efficacy	X	X	X	X	X	X	X		X	X					X
		Equity-related policies and investments	X	X	X	X			X		X	X	X	X			X
		Local government policy capacity		X	X	X		X	X	X	X						
	Ecological and natural systems	Water, soil, ecological systems		X	X	X	X	X	X	X	X	X					
		Weather and climate		X			X				X						
		Natural hazards		X	X	X	X			X	X						
	Physical infrastructure and food systems	Access	X	X	X	X	X	X	X	X	X	X	X	X			X
		Consumption		X	X	X	X	X	X	X	X	X	X	X	X	X	X
		Distribution and production	X	X	X	X	X		X	X	X	X	X	X	X	X	
		Disruption and failure		X	X		X		X		X						
	Urban form and design	Density	X	X	X	X	X		X		X	X	X	X			X
		Land use	X	X	X	X	X		X	X	X	X	X				X
		Spatial design	X	X	X	X	X		X		X	X	X	X			

(Continues)

TABLE 2 (Continued)

			Reviews and frameworks								*Planning reports*				*Data tools*		
			Dempsey et al., 2011	GPSC, 2018	ISO, 2018	Lynch et al., 2011	NASEM, 2016	O'Neill et al., 2018	Science for environment policy, 2015	UN DESA, 2007	City of New York, 2011	Coalition for a Livable Future, 2007	Mile High Connects, 2011	Partnership for Southern Equity, 2017	CA OEHHA, 2018	US EPA, 2019	PolicyLink & USC, 2020
Outcomes	**Environmental sustainability**	Local in-boundary pollution and degradation	X	X	X	X	X	X	X	X	X	X		X	X	X	X
		Transboundary footprints		X	X	X	X	X	X	X	X			X			
	Health	Objective health outcomes	X	X	X	X	X	X	X	X	X	X	X	X	X		X
		Health risks	X	X	X	X	X		X	X	X		X	X	X	X	X
		Health behaviors								X	X		X	X			
	Subjective well-being[b]		X	X		X	X	X									
	Economy and security[b]			X	X	X	X		X	X	X	X	X	X	X		X
Equity			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

[a]Coverage (indicated by an "X" in the table) indicates that the reference in each column discusses, analyzes, or provides data in relation to at least one layer within the SEIU–EHWE data framework category or sub-category in each row.

[b]Coverage for subjective well-being outcomes and economic security outcomes are presented at the category level (rather than at the sub-category level as for the other determinants and outcomes in the table) as defining metrics within these outcomes represents an emerging area of research.

- ***Social actors and social provisioning systems (S)****. Social actors* include individuals and households, businesses, and policy actors (Ramaswami et al., 2012). Individuals and households are described using *basic demographic* characteristics (e.g., race/ethnicity, income, language). Businesses are represented via *basic economic* features, such as employment and economic structure. Policy actors include governmental and non-governmental actors. Measures of governance include *community collective efficacy*, which combines measures of social cohesion/social capital with engagement (Sampson, 2017), and has been linked with a range of outcomes such as safety and resilience after disasters (Cagney et al., 2016) and community health (Cohen et al., 2006). Additional measures of governance include *policy capacity* of local governments, although standard measures are still nascent (Hsu, 2015; Wu et al., 2015), and data on *investments and policies* related to underserved populations across different sectors. *Social provisioning systems* include soft infrastructure or community assets to meet residents' needs, across multiple sectors, including healthcare, education, safety, economy and finance, culture and community, and governance (Ramaswami, 2020). Relevant data attributes include measures of distribution as well as access, for example, to healthcare and education.
- ***Ecological and natural systems (E)*** cover aspects of physical systems in the natural environment (in contrast to engineered built environment and infrastructure), such as ecological, hydrological, and meteorological systems. Examples of data attributes include local temperature, climate zones, soil type, and tree canopy cover, as well as local measures of ecosystems and biodiversity, which have been linked with social, economic, and physical infrastructure inequities in cities (Schell et al., 2020).
- ***Physical infrastructure and food systems (I)*** encompass the physical provisioning systems across eight sectors of infrastructure (i.e., water, waste, energy, food, mobility, buildings, communication, and public space; Ramaswami, 2020) to meet residents' needs. Examples include measures of *access* (e.g., population with access to electricity), *consumption* (e.g., energy use), *production and distribution systems* (e.g., configuration of energy systems spanning generation, transmission, and distribution), and *disruption and failure* (e.g., electricity outages) across the eight infrastructure sectors. To fully inform social equity, it is also important to gather data on *investments and policies* related to underserved populations for each sector (e.g., low-income energy assistance programs, nutrition assistance, rebates for Wi-Fi access, rent forgiveness).
- ***Urban form and design (U)*** describe the physical form of the built environment (Clifton et al., 2008; Cervero & Kockelman, 1997). Examples of data attributes include measures of built environment *spatial design* (e.g., sidewalk width, building height, distance to central business district), *density* (e.g., population density, road network density, job density), and *land use* (e.g., residential and industrial parcels).

3.2 | Categories of desired societal outcomes

The four categories of *desired societal outcomes* are: environmental sustainability (*E*), health (*H*), subjective well-being (*W*), and economy and security (*E*), collectively termed *EHWE outcomes*, and defined as follows:

- ***Environmental sustainability (E) outcomes*** encompass *local in-boundary pollution and degradation* as well as *transboundary footprints*. Local in-boundary data attributes include measures of water, air, and soil pollution. Transboundary footprints can be computed as derived indicators from urban metabolic data, for example, GHG emissions footprints, material use footprints, water footprints, and land footprints (Chavez & Ramaswami, 2013; Ramaswami et al., 2008; Tessum et al., 2019; Wiedmann et al., 2015).
- ***Health (H) outcomes*** are represented by multiple objective dimensions of human health (WHO, 1946) as well as risks to health and safety, such as used in the Global Burden of Disease studies (GBD, 2017). Measures of *objective health outcomes* include premature mortality and morbidity, for both communicable (e.g., COVID-19, tuberculosis, HIV) and noncommunicable (e.g., asthma, cancer) diseases, while derived indicators include lost life years and life expectancy. Measures of *health risks* include exposure to environmental pollution, natural disasters, and traffic-related injuries. Additionally, measures of *health behaviors* include smoking and physical activity.
- ***Subjective well-being (W) outcomes*** describe how a person thinks or feels about their life. Subjective well-being is defined as judging life positively (evaluative well-being) and frequently experiencing pleasant emotions (emotional well-being) (CDC, n.d.) and is determined from surveys (Diener et al., 2002). *Cognitive/evaluative well-being* captures how people think about their lives, often measured on a Cantril Scale (Cantril, 1965). *Emotional well-being* assesses net affect—that is, the net sum of positive emotions such as happiness and negative emotions such as sadness or anger. Measurements of cognitive and emotional well-being, as well as *life purpose*, have increasingly converged in standardized national survey instruments (Helliwell et al., 2012), including the World Happiness Report (Helliwell et al., 2020) and in census surveys conducted in some countries (e.g., UK; ONS, 2020).
- ***Economy and security (E) outcomes*** address wealth, livelihoods, and safety and security, including from natural hazards (MEA, 2005). For economic outcomes, gross income per capita remains a valuable metric, even as it is recognized as an insufficient indicator of human well-being, hence the use of subjective well-being assessments (Helliwell et al., 2012). Basic outcome metrics for economic security, which are also noted as social (*S*) determinants, include the percentage of the population that is below the poverty level. Additionally, objective metrics of security relevant to meeting basic needs (e.g., energy security; Bhatia & Angelou, 2015) are also noted as infrastructure (*I*) determinants. Security from natural hazards is closely related to *resilience*, defined variously as both a latent feature and an outcome. No consistent set of objective metrics for resilience or sustainable livelihoods have emerged, with recent literature suggesting subjective assessments of resilience (Jones,

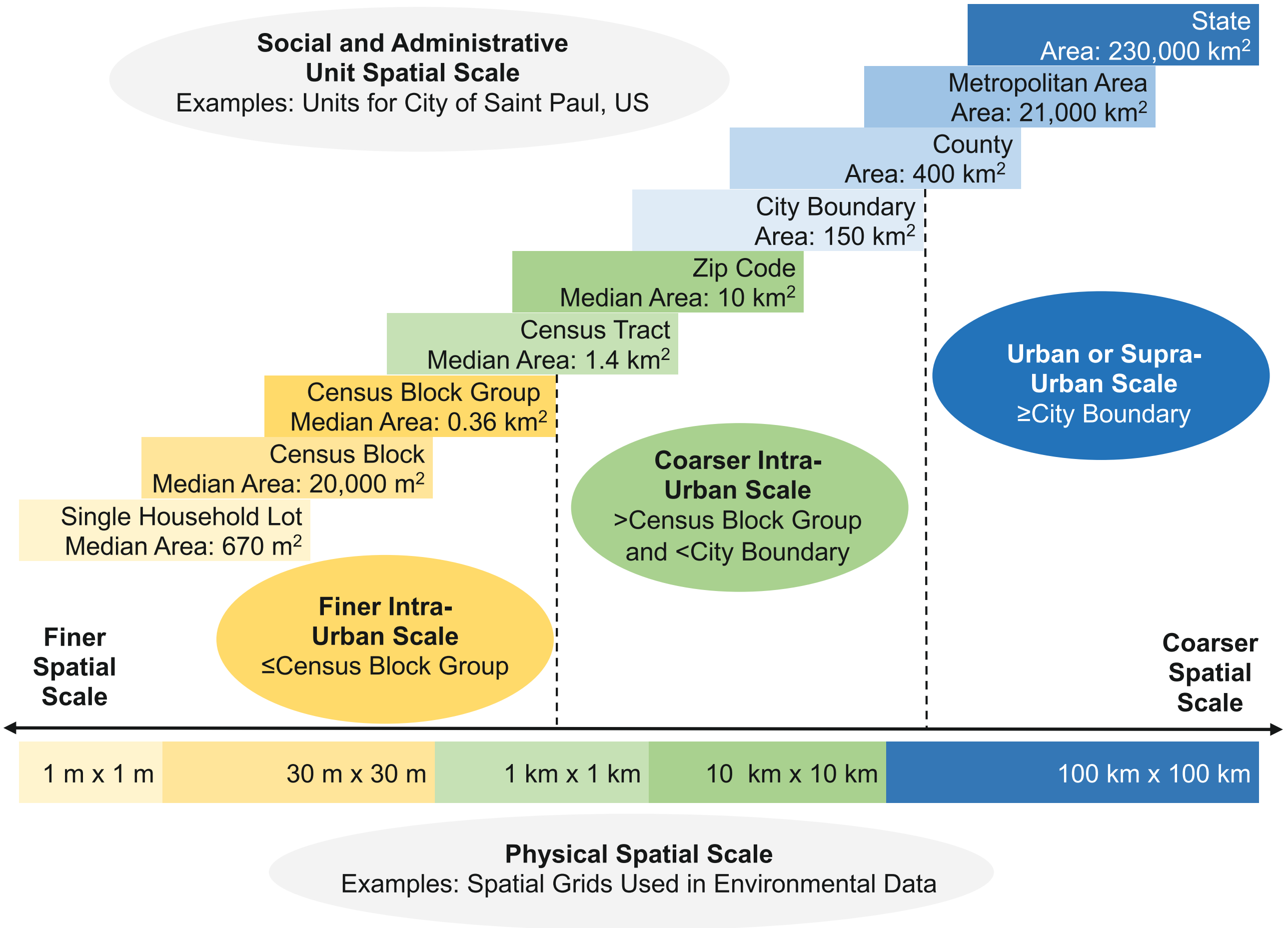

FIGURE 2 Schematic representation (not drawn to scale) of illustrative **social and administrative unit spatial scales** (top panel; with example area data for spatial units for the City of Saint Paul, Minnesota, US) and illustrative **physical spatial scales** (bottom panel; with example spatial grid dimensions used in mapping environmental data), categorized as **finer intra-urban**, **coarser intra-urban**, or **urban or supra-urban** spatial scale

2019) and livelihoods/deprivation (Chambers, 1995; Krantz, 2001). Measures of economy and security (*E*) outcomes are an evolving topic of research.

4 | SYNTHESIS REVIEW OF AVAILABLE INTRA-URBAN SEIU–EHWE DATA IN A CASE STUDY CITY

We reviewed the availability of data for assessing intra-urban social inequality using the SEIU–EHWE data framework described in Section 3 for the case city of Saint Paul, USA. We used search terms from Table 1 and reviewed sources in Table 2 to identify spatial data attributes shown in Table S1 in the Supporting Information. Table S1 represents a snapshot of publicly available data in 2018, at the start of the case studies described in Section 6, and is not intended to be comprehensive given the rapid evolution of data.

We categorized the data attributes in Table S1 based on the finest spatial scale publicly available, important to inform social inequality. We defined finer and coarser intra-urban spatial scales as illustrated in Figure 2:

- ***Finer intra-urban scale*** refers to Census block group (CBG) scale or finer, wherein CBG represents the finest spatial scale at which detailed social (*S*) data (e.g., race/ethnicity, income, education, language) are widely publicly available in the United States. Such social data are essential to evaluate social inequality. CBGs have amorphous boundaries that overlay spatial grids, wherein ecological (*E*) and environmental sustainability (*E*) data (e.g., temperature, air pollution) are often modeled or sensed. Examples include CBG scale and finer social and administrative units (e.g., CBGs, Census blocks, parcels, households), spatial grids with 100 m resolution, point data (e.g., locations of schools), and line data (e.g., road networks).
- ***Coarser intra-urban scale*** refers to larger than the CBG scale but finer than the boundary of the city or metropolitan area. Examples include Census tracts, zip codes, spatial grids with 1 km resolution, and some natural boundaries (e.g., watersheds).

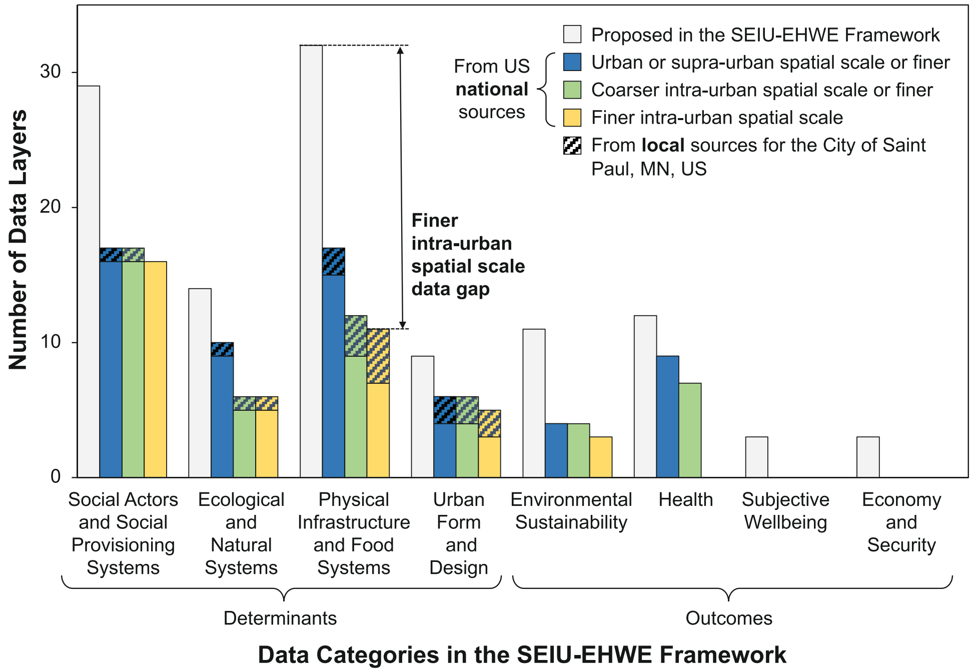

FIGURE 3 Illustrative synthesis of available spatial data at different spatial scales for the city of Saint Paul, Minnesota, US. Availability of data is measured by the number of data layers within each of the data categories in the SEIU–EHWE framework with at least one available data attribute from national sources (with broad coverage of US cities), as well as the number of additional layers with at least one available data attribute from local sources (with coverage for the city of Saint Paul). Finer intra-urban spatial scale refers to the CBG scale or finer

- ***Urban and supra-urban scale*** refers to the urban scale or coarser. Examples include counties, states, metropolitan statistical areas, spatial grids with 10 km resolution, and some natural boundaries (e.g., climate zones).

With these definitions, Figure 3 provides a synthesis of available data and data gaps by SEIU–EHWE category. As illustrated in Figure 3, data availability varied substantially, with greater availability of data at finer spatial scales for SEIU determinants compared to EHWE outcomes.

For SEIU determinants, there was greater coverage of social (*S*) determinants related to basic demographic and economic characteristics through the Census. Across the physical infrastructure (*I*) sectors, Census data provide information on access, while consumer surveys inform consumption, although the latter is not specifically available with intra-urban granularity. Likewise, finer-scale data on disruption and failure of infrastructure are not publicly available for many sectors. Similarly, for infrastructure distribution networks, visible finer-scale data on mobility (e.g., road and sidewalk networks) and on buildings (e.g., housing) are available from national and local sources. For other sectors (e.g., food, energy, waste), finer-scale data on distribution networks are either limited or not in the public domain, often due to security concerns.

For EHWE outcomes, local pollution (*E*) data are publicly available for finer spatial scales, for certain pollutants, through monitors, models, and satellite-based observations. Similarly, national surveys and models provide health (*H*) data for noncommunicable diseases and health behaviors at coarser intra-urban scales. In contrast, subjective well-being (*W*) data are not available at intra-urban scales. As noted in Section 3, there are no well-accepted metrics for economy and security (*E*) as this is an active research area.

Overall, Table S1 of the Supporting Information documents 103 spatial data attributes available from public national sources and 13 from local sources (primarily via local government open data initiatives). Of these, 56 are available for finer spatial scales. These open fine-scale data support the analysis of intra-urban inequality for diverse determinants and outcomes. However, we also identified data gaps. We did not find available finer-scale data for 72 of the 113 data layers of interest in Table 1. These gaps reveal important data science research priorities to comprehensively assess intra-urban social inequality.

5 | METRICS AND DATA ANALYTICS FOR MEASURING INTRA-URBAN INEQUALITY

A number of metrics and analytic approaches are available to quantify social inequality across the SEIU determinants and EHWE outcomes. These methods can be categorized as "spatial" or "non-spatial" (Table 3).

Non-spatial measures of inequality, such as the Gini coefficient (Glaeser et al., 2009; Jacobson et al., 2005) and quantile ratio (e.g., P80/P20 refers to the ratio of the 80th percentile to the 20th percentile value) among others (e.g., reviewed in Harper et al., 2013), serve to describe dispersion and extremes, respectively. These measures of inequality describe the "spread" of single attributes, such as income. Other measures of inequality

TABLE 3 Methods of analysis and example metrics for intra-urban inequality across SEIU determinants and EHWE outcomes

Methods of analysis		*Example metrics for intra-urban inequality*
Non-spatial	Single variable analysis of inequality in urban determinants and outcomes (e.g., income, housing size, health risks)	Measures representing dispersion and inequality for a single variable: • Relative standard deviation • Gini coefficient • Inter-quantile percentile ratios (e.g., P80/P20) and share ratios (e.g., S80/S20)
	Analysis of impact of social stratification (e.g., by race, income, gender) on another outcome variable (e.g., health risks)	Measures of differences in outcomes for groups with different socioeconomic status: • Disparity ratios of an outcome variable between groups with different socioeconomic status • Significance tests for differences in the mean of an outcome variable between groups with different socioeconomic status
	Multi-variable regression analysis (not explicitly spatial) to understand relationships between outcomes and socioeconomic determinants	Measures of relationships between outcomes and socioeconomic determinants from regression models: • Coefficient or elasticity estimate from groups with different socioeconomic status • Stratified regression model parameters (e.g., by income) • Interaction terms in regression models (e.g., between race and income)
Spatial	Spatial statistics for cluster detection and analysis across geographies characterized by socioeconomic features (e.g., poverty, language)	Measures of relationships between spatial clusters (e.g., "hotspots") in outcomes and socioeconomic features: • Indicators of spatial clustering in single outcome variables (e.g., Moran's Index) • Identification of spatial clusters (using, e.g., *k*-means or nearest neighbor analyses) in outcome variables • Comparison (e.g., using mean) of socioeconomic variables across different spatial clusters in outcomes
	Spatially explicit models to understand relationships between outcomes and socioeconomic determinants	Measures of relationships between outcomes and socioeconomic determinants from models accounting for spatial dependencies, such as from: • Spatial autoregressive models • Conditional autoregressive models • Spatial agent-based models

quantify differences or disparities of various attributes across two or more social groups (e.g., groups with different income levels or racial/ethnic backgrounds) relevant for understanding social equity (Braveman et al., 2010; Adam et al., 2013). Examples include disparity ratios in health risks for low- versus high-income groups. Social equity seeks to reduce disparities experienced by socially disadvantaged populations, for example, by race, ethnicity, gender, language, or income, among others (Braveman, 2006).

Because multiple determinants together shape the EHWE outcomes, multi-variable regression is commonly used to unpack determinants (e.g., Cook & Manning, 2009; Greenman & Xie, 2008). Statistically significant correlations with respect to, for example, race/ethnicity, gender, or income factors from generalized linear regression models can be used to identify social inequalities in outcomes. When different social attributes, such as race and income interact, methods to unpack them are applied, including stratification (Mitchell et al., 2016) and interaction (Nuru-Jeter et al., 2018; Ward et al., 2019).

Spatial analysis methods are applied to measure social inequalities while accounting for spatial dependencies in SEIU and EHWE data. Methods include cluster detection and spatial multi-variable models. Cluster detection can identify locations of "hot spots" in single variables (e.g., in tree canopy cover or pollution levels). Such clusters can then be combined with relevant social data (e.g., income) to assess inequalities. Metrics such as Moran's Index (and others; Schabenberger & Gotway, 2005) provide evidence of clustering while methods such as *k*-means (and others reviewed by Saxena et al., 2017) identify the clusters themselves. Spatial models, which include conditional autoregressive models (and others; Banerjee et al., 2015), are used and interpreted similarly to other multi-variable models (Table 3), but account for spatial dependence in the data. This allows inequalities to be identified more accurately in the presence of spatial dependence.

6 | CASE STUDIES MEASURING INTRA-URBAN INEQUALITY AND EQUITY USING SEIU–EHWE DATA

This section highlights four application case studies that demonstrate how the analytic methods in Section 5 can be applied to finer intra-urban spatial data using the SEIU–EHWE framework to inform real-world questions of social inequality and equity.

6.1 | Case study 1: Intra-urban equity in participation in residential energy efficiency programs and in energy service disruption in Tallahassee, Florida, US

This case studies multiple physical infrastructure (*I*) sectors (energy and communication), addressing consumption, as well as disruption during storms, with documentation of investments across social (*S*) groups to help quantify social equity at fine spatial scales in Tallahassee, Florida. Because household-level social data were not publicly available, researchers worked with local utilities by geocoding property tax data to extract housing values, voting registration data to extract residents' race, age, and political party affiliation, and substituting missing data (e.g., income and education) from the Census. This household-level social data set was then combined with data from the local utility on energy program investment and participation (Curley et al., 2020) and service recovery after disruptions (Xu & Tang, 2020) for all households in Tallahassee.

Researchers applied logistic regression to analyze household-level participation in various energy programs (e.g., loan, efficiency, rebate, and audit) (Curley et al., 2020). They found that while all of the energy programs reduced energy bills, loan and rebate programs had higher participation from wealthier households whereas the auditing program had higher participation among racial minority households and households with higher energy burdens, informing the more equitable design of energy programs. The study of disruptions (Xu & Tang, 2020), consistent with the previous literature (Olshansky et al., 2012), found that racial minority households generally experienced longer service disruptions, even though racial minority households also experienced a higher level of need for those services (Elliott & Pais, 2006). However, racial minority households were more likely to use the 311 smart platform to submit requests for power restoration, indicating that the use of e-governance technologies may help narrow the racial equity gap for service delivery time.

6.2 | Case study 2: Intra-urban equity in residential energy use and in energy efficiency investment in Saint Paul, Minnesota, US, and Tallahassee, Florida, US

This case analyzed inequality in energy use and energy efficiency investment by race and income in Saint Paul and Tallahassee (Tong et al., 2021). Fine spatial-scale data on infrastructure (*I*), specifically energy use across social (*S*) groups, along with data on the distribution of energy efficiency rebate investments (representing social [*S*] equity-related policies and investments), were gathered in Saint Paul (Census block level) and Tallahassee (premise level) through partnership with utilities under a non-disclosure agreement. For both cities, Census block level energy use and investment data were merged with other SEIU determinants (including race/ethnicity, income, tree canopy, and building characteristics) from publicly available sources, such as the Census and tax assessors' data.

First, this study computed Gini coefficients and disparity ratios by race and income for energy use per household and energy use intensity (EUI) by floor area across three spatial scales of data aggregation (i.e., Census block, block group, and tract). These metrics revealed intra-urban inequalities in energy use by race and income. For example, heating/cooling EUI disparity ratios between the lowest- and highest-income CBGs were up to 2.65 in Saint Paul, and heating/cooling EUI disparity ratios by race within the lowest-income CBGs were up to 2.56 in Tallahassee. Second, this study applied linear regression analysis using CBG data to unpack relationships between EUI, race, and income, along with other SEIU determinants. Statistically significant parameters included social (*S*) (e.g., income, race), infrastructural (*I*) (e.g., single- vs. multi-family floor areas), and ecological (*E*) (e.g., tree canopy) determinants. Third, this study evaluated the proportion of funds invested in the different CBGs against the proportion of energy used and the percentage of underserved households represented, to quantify the extent to which funds were equitably allocated to disadvantaged groups, representing a first quantitative metric of intra-urban equity in energy sector investments. Thus, this case illustrates the use of fine-scale SEIU data and inequality metrics to inform a more equitable distribution of energy sector investment.

6.3 | Case study 3: Intra-urban energy use modeling in Atlanta, Georgia, US

This case explored residential energy use patterns for natural gas and electricity considering multiple SEIU determinants in metropolitan Atlanta (Lawal et al., 2021). Energy use data for electricity and natural gas (infrastructure [*I*] consumption attributes) were obtained from utilities at the zip-code level and matched with social (*S*) (e.g., income, education), urban form (*U*) (e.g., impervious surface), and environmental sustainability (*E*) data (i.e., air pollution concentrations from a fine-grained model). Non-spatial regression models were developed to evaluate correlations between energy use and SEIU determinants for residential electricity and natural gas use. These models indicated that natural gas use depended largely upon specific social (*S*) determinants (i.e., income and household makeup), whereas electricity use depended on a wider range of SEIU determinants. Further spatial analyses (incorporating geo-spatial mapping, principal component analysis, and *k*-means clustering) revealed a distinct spatial pattern: residential electricity use correlated with air pollution concentrations and road networks. Thus, mapping of fine-scale SEIU data, combined with additional regression modeling and spatial analysis tools, indicated that local air pollution and road networks had a strong association with increased urban residential electricity use. This case study demonstrates how a multi-sector analysis using fine-scale data can reveal unexpected associations among SEIU attributes.

6.4 | Case study 4: Intra-urban inequality in air pollution exposure and health outcomes in Atlanta, Georgia, US

This case applied spatial analysis tools to investigate social equity in air pollution exposures and health (*H*) outcomes in metropolitan Atlanta (Servadio et al., 2019). Previous works have noted connections between air pollution exposure and health (Bourdrel et al., 2017), and others have highlighted inequities in air pollution exposure (Stuart & Zeagar, 2011), but these had not been previously assessed together at intra-urban spatial scales. This case gathered SEIU determinants data and combined them with exposures to two air pollutants (i.e., nitrogen dioxide and fine particulate matter) and four health (*H*) outcomes (i.e., asthma, chronic obstructive pulmonary disease, coronary heart disease, and stroke prevalence) at the Census tract level. Values of Moran's I, evaluated for each of the health outcomes and air pollutant exposures, showed strong evidence of spatial clustering. Conditional autoregressive models indicated that Census tracts with majority African American populations had a significantly higher prevalence of each health outcome as well as significantly higher air pollution exposure. This study quantified existing intra-urban social inequities in both the exposure and outcome of an established health mechanism.

7 | DISCUSSION AND FUTURE DIRECTIONS FOR RESEARCH AND PRACTICE

We created a fine spatial-scale SEIU–EHWE data framework to evaluate social inequality and equity in complex urban systems (Figure 1). We then applied the framework through four case studies in different US cities addressing multiple SEIU determinants and EHWE outcomes. The case studies represent diverse practical applications, from energy consumption to energy disruptions during storms, to air pollution exposure and health outcomes. Together, these case studies demonstrate how the framework can provide clarity and consistency on the collection of relevant data at fine spatial scales. They also demonstrate how the analysis of such fine-scale data can provide actionable information to advance social equity in sustainable urban systems.

As demonstrated by the case studies, the framework can serve as a guide for investigating interactions among multiple sectors, determinants, and outcomes. Examples of such interactions include complex interactions (e.g., the influence of multiple SEIU determinants on subjective well-being outcomes; Das, 2020), reverse interactions (e.g., the impact of air pollution outcomes on solar energy production determinants; Bergin et al., 2017), positive feedback interactions (e.g., mutually reinforcing relationships between subjective well-being and health behavior outcomes; De Neve et al., 2013), and cross-scale interactions (e.g., the influence of tree canopy on the temperature at different spatial scales; Ziter et al., 2019). Future work can explore additional interactions and their implications for distributional inequality.

Additionally, future work can apply the framework to investigate the causal mechanisms historically shaping inequality in cities and to model future scenarios and their potential equity impacts. Implementing the framework across large numbers of cities can help identify which aspects of inequality are place specific and which are generalizable across cities. Overall, the framework can serve as an organizational tool for gathering fine spatial-scale data for various applications addressing intra-urban inequality.

We investigated the availability of fine spatial-scale SEIU–EHWE data, for example, US city, and found substantial gaps (Figure 3). These data gaps help identify priorities for future urban data research and database development. One approach to address these gaps is through innovative data science methods, such as advanced modeling (Chaudhary et al., 2016), community science (Filippelli et al., 2018; Li et al., 2019), crowdsourcing (Zheng et al., 2018), digital imagery (Demuzere et al., 2020; Suel et al., 2019), satellite-based observations (Román et al., 2019), and low-cost sensor networks (Caubel et al., 2019). A second approach is through data-sharing partnerships and co-production (Norström et al., 2020). Two of the case studies demonstrate such partnerships, filling key gaps needed to assess social equity in urban energy systems (Tong et al., 2021; Xu & Tang, 2020;).

Data availability was sparse in the example US city and can be even sparser in more resource-limited locations. Global cities would also have different administrative boundaries (Figure 2) and other relevant social data for assessing social inequality (Table 1), as illustrated by SEIU determinants' databases for cities in India (e.g., Asher & Novosad, 2019; Tong et al., 2021).

Given the importance of addressing inequality in multiple urban agendas—from climate change to public health—there is an urgent global need for open data at fine intra-urban spatial scales. This fine-scale data can be analyzed to inform, for example, targeted investments to advance equity. Such applications can enable a more equitable design of infrastructure, investments, policies, and outcome assessment protocols toward a more sustainable and equitable future.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All data are in the supporting information of this article.

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