Optimising for equity: Sensor coverage, networks and the responsive city

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Abstract

Decisions about sensor placement in cities are inherently complex, balancing structural inequalities with the differential needs of populations, local stakeholder priorities and the technical specificities of the sensors themselves. Rapid developments in urban data collection and Geographic Data Science have the potential to support these decision-making processes, yet even the most cutting-edge algorithms cannot deliver on complete and equitable sensor coverage. Focusing on a case study of air-quality sensors in Newcastle-upon-Tyne (UK), we employ spatial optimisation algorithms as a descriptive tool to illustrate the complex trade-offs that produce sensor networks that miss important groups—even when the explicit coverage goal is one of equity. The problem is not technical; rather it is demographic, structural and financial. Despite the considerable constraints that emerge from our analysis, we argue the data collected via sensor networks is of continued importance when evidencing core urban injustices (e.g., air pollution or climate-related heat). We therefore make the case for a clearer distinction to be made between sensors for monitoring and sensors for surveillance, arguing that a wider presumption of bad intent for all sensors potentially limits the visibility of positive types of sensing. For the purpose of monitoring, we also propose that basic spatial optimisation tools can help to elucidate and remediate spatial injustices in sensor networks.

1. Introduction

Surveillance is a core concern when it comes to smart city sensor technologies (Kitchin et al. 2015). The increasing ubiquity of sensors in the urban environment means that citizens are subject to much greater levels of scrutiny than ever before (Kitchin 2016). Sensor technologies can underpin, on the one hand, a growing “surveillance economy” that exploits personal data to generate profit (Zuboff 2015), and on the other, discriminatory policing practices informed by Big Data (Furguson 2019). As such, the aims of speed and convenience that typify today’s “fast infrastructures” create ease for some and harm for others, exacerbating social and environmental crises around the world (Barlow and Drew 2020). Understandably, surveillance-orientated sensor technologies that collect data *about* people have attracted considerable critique (Kitchin et al. 2015; Kitchin 2019; Crawford and Schultz 2014; Barocas and Nissenbaum 2014; Sadowski and Pasquale 2015).

Often attracting less attention are those sensor technologies that have the potential to generate data *for* people. Sensors that fulfil a monitoring function can play an important role in evidencing environmental injustices (Mah 2017), including poor air quality (Mitchell and Dorling 2003) or excessive urban heat (Sanchez and Reames 2019). Monitoring sensors provide evidence of the disproportionate exposure of selected populations to urban ills (Grineski and Collins 2018; Nadybal et al. 2020), and the ways in which they can be displaced by changes in policy. Without monitoring, these spatial environmental injustices remain invisible. Frustratingly, the two types of sensors—surveillance and monitoring—are often integrated within smart city platforms that include, for example, sensors recording both air quality and footfall. The wider presumption of bad intent for *all* sensors (irrespective of purpose) limits the visibility of positive types of sensing in critical smart urbanisms and—importantly—hinders our capacity to ensure that monitoring networks are deployed equitably for all urban inhabitants.

This is not to say that sensors that collect data *for* people cannot generate or perpetuate injustice. Indeed, just because a sensor is “good” in principle does not mean that it is generating good sensor coverage in practice. Unjust technologies are both a symptom *and* a cause of injustice and it is well understood that smart- or data-orientated injustices are driven by the uneven social processes that inform the selection and design of technologies (Crampton 2020; Benjamin 2019). Rather, it is instead to recognise that some types of sensors have the potential to do important work for social justice, when underpinned by social processes that seek to bring about equitable change in cities, or to evidence and challenge disadvantage or discrimination.

With this potential in mind, our analysis works within the constraints of existing infrastructures and decision-making algorithms, reorienting the social processes that inform monitoring sensor technologies, and especially their placement, to concentrate on equity. Our approach emphasises the trade-offs inherent to sensor locations, particularly where demographic coverage is concerned. We adapt widely-accepted spatial optimisation algorithms to show how conceptualisation of coverage, density of network, and spatial sorting of inhabitants have important equity impacts that limit the capacity for networks to be judged truly inclusive or just. We illustrate our approach with a case study of air quality sensors in Newcastle-upon-Tyne, United Kingdom (UK) (hereinafter Newcastle). Newcastle is home to the Urban Observatory (UO), an extensive network of sensors which provides the “largest set of publicly available real time urban data in the UK” (UO 2021). Using Newcastle as a case study allows for comparison between an “actually existing” sensor network and the sensor networks estimated in our analysis (Shelton et al. 2015).

Our results highlight some of the ways in which—even with the best of intentions—urban decision-makers are limited in their capacity to develop equitable sensor networks. Inequities in sensor networks need not be underpinned by unjust, or biased social processes; even when optimising for equity, sensor networks are likely to miss important sub-groups (and locations). Despite the considerable constraints of our resultant sensor networks, we argue that the “just good enough” (Gabrys et al. 2016), or “satisficing” (Herbert 1955), data produced still has the *potential* to play a valuable role in evidencing core urban injustices and supporting transparency in the decision-making process. The paper is structured as follows. We first discuss the different purposes of sensor infrastructures: sensors for surveillance and sensors for monitoring (Sect. 2). Section 3 explores the trade-offs in sensor placement before outlining our methodological strategy in Sect. 4. We then discuss the networks that emerge from our analysis and the trade-offs associated (Sect. 5) before concluding with a discussion about the ways in which we might reimagine the use of sensors in cities (Sect. 6).

2. Surveillance Versus Monitoring: What Are Sensors For?

A socio-technical perspective understands the relations between social structures and technical systems as mutual and co-productive, with an emphasis on contextualising these relations in both space and time. Sensor technologies and networks therefore can—and should—be understood as intertwined with society. Political and socio-economic structures within society influence the formation of smart cities and associated infrastructures, and *vice versa* (Graham and Marvin 2001). In this way, sensor technologies are the outcome of the complex social relations that flow through them—social relations that shape the design, placement, and use of sensors, to fulfil different purposes. In the section that follows we distinguish between sensors for the purpose of surveillance, and sensors for monitoring.

2.1. Sensors for Surveillance

Surveillance is a core concern when it comes to smart cities and technologies (Kitchin et al. 2015; Kitchin 2019; Crawford and Schultz 2014; Baracos and Nissenbaum 2014; Sadowski and Pasquale 2015; Zuboff 2015). Subsequently, sensors that collect data *about* people have attracted considerable critique. A growing “surveillance economy”, generating profit from personal data has emerged (Zuboff 2015). New sensor technologies, the frictionless flow of data, and sophisticated urban analytics have attracted greater levels of private sector involvement in both the commissioning and funding of sensor networks. This has led to ethical concerns about the ways in which value can be extracted from data generated, and the potential for new data to inform urban governance processes (Kitchin et al. 2015; Sadowski and Pasquale 2015).

Such datafication is also coupled with concerns about privacy. People are subject to intensified scrutiny as their daily lives are increasingly captured as data (Dodge and Kitchin 2005), including geo-location or tracking technologies such as CCTV, facial recognition, traffic flow monitoring and spending patterns, especially when used commercially (Kitchin 2016). The use of multiple and interacting systems run by a variety of commercial and state actors means that consent is increasingly diluted, or lost (Baracos and Nissenbaum 2014; Solove 2013). As new forms of urban governance based on datafication tend to inherit public trust, it is not always clear how new forms of data are produced and used, and whether individuals have the capacity to change these processes (Jameson et al. 2019; Lagoze 2014; Michael and Lupton 2016).

Issues of surveillance are further compounded by the tendency for the systems and technologies upon which such practices are founded to discriminate (Ferguson 2019). As argued by Benjamin (2019), the basic conditions for creating technology are racist. Differential policing and surveillance based on demographics has attracted particular attention in this regard. In their recent book, *Data Feminism*, D'Ignazio and Klein (2020) highlight how important societal decisions are increasingly made by automated systems systematically analysing large volumes of information. D'Ignazio and Klein cite the example of PredPol, a predictive policing company founded in 2012 that has informed the policing practices of the City of Los Angeles for almost a decade. PredPol's predictive policing is predicated on historical crime data, therefore reproducing the enduring discriminatory practices that have resulted in the disproportionate policing and surveillance of neighbourhoods of color in the United States (see also O'Neil 2016). The case of predictive policing illustrates how specific groups within the city have the *privilege of invisibility* from sensors deployed with the purpose of surveillance, versus those sub-groups who are not afforded that privilege.

2.2. Sensors for Monitoring

In response, Kitchin (2016; 2018) argues that, whilst they have the potential to provide new and useful insights into cities and systems, smart cities and urban science need to be re-imagined and re-cast. Grassroots environmental justice activists have increasingly used Big Data techniques for monitoring and evidencing toxic environmental exposures, and “taken science into their own hands” (Mah 2016, 123). The potential for sensors for monitoring purposes has been discussed most extensively in relation to citizen sensing, typically using low-cost sensors (e.g., Gabrys et al. 2016; Corburn 2005; Pritchard and Gabrys 2016; Gabrys 2016). Gabrys et al. (2016) evidence how citizen sensing gives rise to alternative ways of creating, valuing, and interpreting datasets. Using low-cost sensors, indicative monitoring can be undertaken, generating data for a wider spatial area. For example, low cost, distributed sensor networks are used to evidence the distribution of air pollution at a higher spatial and temporal resolution (e.g., Cao et al. 2020; Feinburg et al. 2019). The resultant “just good enough data” often falls outside recommended standards of scientific data (e.g., evaluating statutory air quality targets) (Lagoze 2014). However, the data opens up new “political possibilities” (Irwin 1995) by mobilising citizens around common issues, prompting conversations with policymakers, and providing initial evidence for greater investment in regulatory-standard monitoring infrastructure (Gray et al. 2016).

2.3. A Surveillance-Monitoring Continuum

Highlighting the differences between sensors for monitoring and sensors for surveillance is not to say that monitoring sensors that collect data *for* people do not generate or perpetuate injustice. Just because a sensor is “good” in principle (e.g., collecting information about local air quality), does not mean that it is generating good sensor data or coverage in practice. And, of course, many sensors are inherently equivocal or ambivalent in purpose; noise, for example, is a health and wellbeing issue, but can also be used to police populations in contested spaces (e.g. Pablo Bello et al. 2017; Hong et al. 2019). Moreover, sensors that monitor urban challenges are situated within urban environments that are inherently unequal, and technologies tend to replicate this unevenness (Shelton et al. 2015; Dencik et al. 2016; Robinson and Franklin 2020). As such, the data they produce rarely includes everyone equally or in a representative way (Shelton et al. 2015), typically divided based upon existing forms of social difference (race, income, class, ethnicity, age, disability) (Brannon 2017). Mah highlights a need to “avoid over-relying on new digital methods and techniques as a panacea for problems of voice” (2016, p. 130). So, a dilemma exists: sensor technologies have the potential to do important work for social justice, but are constrained by a variety of factors that may include intent and wilful ignorance, but also transparency and access to more sophisticated decision-making support.

3. Trade-offs In The Placement Of Sensors In The City

As recognised by Uprichard (2013), new forms of big data from sensors are not “going to solve our big social problems... [but] it may help to describe them, to picture them in new ways, to visualise the available data differently, and this may help to communicate the problems to more people”. In framing data from sensors in this way, it is useful to draw upon conceptualisations of “just good enough data” (Gabrys et al. 2016) (see Section 2 for further elaboration), as well as the idea of “satisficing” (Simon 1955). The term satisficing has been used extensively in relation to decision-making, placing a focus on decisions that are satisfactory or adequate, as opposed to ideal or optimal. Whilst it is often assumed that decisions are well-defined, and that relevant parameters to inform decision-making are known or can be estimated in a meaningful way (Hansson and Hirsch Hadorn 2018), typically decision-making processes take place under much less systematic conditions—and sensor placement is no exception. Even in a context in which decision-makers have inclusive intentions for the deployment of sensors within a city, limited information and expertise, as well as competing goals, means sensor networks are likely to come up short given the myriad trade-offs involved.

From the outset, trade-offs are embedded in sensor networks as they are rarely designed with a single function in mind. Instead, they seek to address competing requirements from different stakeholders with varied objectives—complicating the decision-making process. As such, real-world sensor networks must try to fulfil several functions simultaneously. This variety of functions has important implications for what constitutes good coverage (Robinson and Franklin 2020). Functions range from hazard-orientated networks that provide coverage of hazard or nuisance producers (for example, poor air quality or noise pollution) to vulnerability-orientated networks that encompass populations most at risk (whether due to health, age or other factors).

In the case of vulnerability-oriented networks, trade-offs also emerge as a result of the spatial demographic structure of the population within a city. Our case study of Newcastle (Figure 1) is one of the UK's Core Cities located in the North East region of England. Here, as in other cities, population sub-groups sort differently across space. Approximately 293,700 inhabitants live within the Local Authority of Newcastle (Newcastle City Council, 2021), the geographic focus of our analysis. Considering the distribution of the total population based on the 2011 Census, density decreases with distance from the city centre; more people can be “covered” by fewer sensors in the city centre, but that, of course, implies a lack of importance of those residing in the urban fringe. Based on the distribution of children (aged below seven years old) their share is lower in the city centre and highest in the major inner suburban areas, especially to the west of the city (Figure 1). In contrast 14.4 percent of the population is aged sixty-five or over (Newcastle City Council 2021). Based on Census 2011, areas with a higher proportion of older persons (persons over sixty-five years old) are spatially concentrated across the suburbs of Newcastle, with lower rates in the centre of the city. By comparison—and recognising that inhabitants are mobile and place of residence an imperfect locational anchor—the population based on place of work reverses many of these spatial patterns, with the city centre and industrial areas on the periphery of the city of greatest importance. Even based on the sub-set of demographic variables presented—chosen here for their relevance where air-quality is concerned—the relative importance of (and subsequent justification for) sensor coverage varies considerably. The point here is that, given differential location patterns of demographic sub-groups, prioritizing coverage or monitoring for some groups is likely to disadvantage other groups, unavoidably—unless financial resources pose no constraint.

And, of course, financial constraints are ubiquitous for local government actors with competing policy priorities, leading to a need to balance what is optimal (i.e., uniform coverage of the entire city) with what is practical. Sensor networks are an expensive investment. This includes the initial costs of the infrastructure itself as well as the legacy of continual maintenance to ensure data is collected effectively and that the data (where openly available) is accessible to wider audiences. Bates (2012) highlights the path dependency in cities when they adopt particular commercial technologies and platforms that cannot easily be undone or adapted. The cost of a sensor also influences the quality of the data collected, with trade-offs to be made between the price and size of the device, and the accuracy and precision of the measurements made. Guidance from the Department for Environment, Food and Rural Affairs (Defra), the department responsible for air quality in the UK, recognises that low-cost sensors may be particularly sensitive to changes in atmospheric humidity and temperature, or provide false signals in response to high concentrations of other air pollutants (Defra 2021). Subsequently, it is advised that low-cost sensors should not subsume the role of reference monitors used in the automatic monitoring network, making monitoring compliance with statutory air quality targets a potentially expensive endeavour (see also Lewis and Edwards 2016). Maintenance work is also a socio-technical effort, involving not just technical know-how about sensor technologies, but also human labour and ingenuity in how sensor infrastructures are “brought to life” (see Strebel 2011, p. 245, discussing maintenance in relation to buildings). Sensors are often embedded within an urban environment that is not fit for purpose, “integrated awkwardly into existing configurations of urban governance and the built environment” (Shelton et al. 2014, p. 14). Sensor placement can also be contested by local actors, not least owing to concern about surveillance discussed (see Section 2). Put briefly, decision-makers face challenges and trade-offs not only about *where* to place sensors, but *how many* to deploy in the first place.

The complex dynamics and trade-offs associated with the placement of sensors merit systematic evaluation prior to placement, however, this process of evaluation often falls short. Instead, at best, sensor placement is typically informed by ad-hoc decision-making in response to specific issues. More often, sensors are deployed by companies on behalf of cities resulting in “a ‘one size fits all smart city in a box’ solutions that take little account of the uniqueness of places, peoples and cultures and thus works sub-optimally” (Kitchin 2018, p. 225). It is important then to evaluate what an “optimal” sensor network might look like, and more broadly whether it is possible to configure a truly equitable sensor network—and what is uncovered or learned through the process. In the analysis that follows, we illustrate how the fundamental spatial optimisation tools employed so widely in quantitative geography can be used by urban decision-makers to assess these trade-offs, and elucidate spatial inequalities, in sensor placement.

4. Optimising Sensor Locations For Demographic Coverage In The “smart City”

4.1. Spatial Optimisation: Greedy and Genetic Algorithms

In the spatial sciences, decision-making about sensor locations and coverage is likely to be thought of as a problem of spatial optimisation. Spatial optimisation algorithms identify the best arrangement or allocation of infrastructures (Tong and Murray 2012). Such methods and tools have burgeoned in recent years due to increasing recognition of the need for an integrated approach to spatial planning to tackle complex societal challenges. A spatial optimisation typically considers a particular geographical problem as a specific objective—for example, maximising population served or minimizing distance to a nearest facility—that is operationalized by way of a set of constraints that capture the decision-making process (e.g., minimizing cost or distance). In our case, sensor placement can be augmented based on multiple objectives, i.e., maximising coverage of a number of vulnerable populations or hazards, or constraints, i.e., minimizing total sensor costs (e.g. Sun et al. 2019).

There are two different approaches to solving a multiple objective problem using spatial optimisation: exact and heuristic. An exact approach exhausts all possibilities to identify the optimal solution to a problem. An exact approach to spatial optimisation (e.g. integer or linear programming) is often limited in its applicability, as increasing numbers of variables leads to an exponential increase in the solution time (Delmelle 2010). Even when solvable, a single solution is often not appropriate when seeking to represent complex, real-world issues. Comparatively, heuristic approaches offer an approximate approach to spatial optimisation, generating one or more good solutions to a problem. To illustrate the challenges associated with providing equitable sensor network coverage, our analysis employs two heuristic approaches for spatial optimisation of sensor placement: a greedy algorithm and a genetic algorithm. In both instances, quality and exactness of results is partially dependent on how geographic space is represented, broken-up, and conceptualised—for example, where points are used to represent a process or how coverage is estimated. This reinforces one of the ways in which spatial optimisation problems are inherently complex to solve.

We begin by employing a **greedy algorithm** to derive optimal sensor networks based on a single objective (i.e., a single demographic variable). Greedy algorithms make the locally optimal choice at each stage of problem-solving, with the overarching aim of quickly finding a solution that is a reasonable approximation of the global optimum. Greedy algorithms iteratively build a solution. In our case, the first sensor in the network is placed at the location that maximizes overall coverage of the city for the given objective. The second sensor is then placed in the location that provides the most additional coverage, leaving the first sensor fixed in its original location. This process is repeated until a network with the desired number of sensors has been generated. Greedy algorithms are critiqued for their tendency to commit to certain choices early in the process, but typically provide a good, yet sub-optimal solution, to a decision (Tong and Murray 2012; Garai and Chaudhuri 2007; Delmelle 2010). We have used our own implementation of a greedy algorithm, taking inspiration from the approach in Sun et al. (2019).

Next, a **genetic algorithm** is used in order to generate optimal sensor networks based on multiple objectives. Genetic algorithms are randomized search algorithms that have been developed to imitate processes of natural selection to search for the optimal or near-optimal solution. Greedy algorithms use techniques inspired by processes of inheritance, mutation, selection and cross over to inform the problem-solving strategy (Holland 1992; Xin-She Yang 2021). Specifically, we have used the implementation of NSGA-II (Deb et al. 2002) in the optimization library pygmo (Biscani and Izzo 2020). This aims to find “non-dominated solutions”—in this context, optimised sensor networks where it is not possible to move a sensor without decreasing the overall coverage of at least one demographic group. Its output is not a single network but rather a spectrum of many networks, each of which represents a unique compromise between the different objectives.

4.2. Formulating the Sensor Coverage Decision Problem

In characterising different spatial optimisation problems, Tong and Murray identify a wide range of spatial features that can be the focus of optimisation: “distance, adjacency, connectivity (contiguity), containment, intersection, shape, districts, and pattern” (2012, 1302). In conceptualising optimal sensor placement, we also add to that list *coverage* (as discussed in Section 3). Coverage, where sensors are concerned, is a complicated concept, dependent on network purpose and perception (Robinson and Franklin 2020).

To operationalise coverage here, we adopt the approach taken in Sun et al. (2019) where the level of coverage at any given location depends on the distance to the nearest sensor and a parameter, Θ , which controls the rate that coverage decays. Formally:

$$c_{ij} = \exp(-d_{ij} / \Theta) \quad 1$$

Where c_{ij} is the coverage at location i provided by a given network of sensors j , and d_{ij} is the distance between location i and the nearest sensor to that location in the sensor network j . The Θ parameter can be thought of as a sensor coverage area, or the size of the neighbourhood surrounding a sensor that is considered to benefit from its placement. For our purposes, two sensor coverage areas are selected for which to derive solutions: 100 metres and 500 metres (also described as $\Theta = 100$ metres and $\Theta = 500$ metres). The smaller value of 100 metres provides a more realistic estimate of the distance within which a sensor is likely to provide accurate information (i.e., data recorded by a sensor is only truly accurate for areas near a sensor). In practice, this figure is likely to be even lower depending on the quality of the sensor infrastructure and the characteristics of the local built environment. The larger value of 500 metres provides a perhaps more realistic picture of the granularity a decision-maker might attempt to achieve

when planning sensor coverage across a large urban conurbation, especially when thinking beyond data quality to consider sensor coverage as an issue of representation (Robinson and Franklin 2020)^[1].

Our analysis emphasises the different ways in which decision-makers might prioritise sensor coverage if they were to take a demographic approach—that is, prioritising coverage of different subsets of the population. We estimate and compare four contrasting conceptualisations of demographic sensor coverage: (i) coverage of the total residential population; (ii) coverage of residents under sixteen (children); (iii) coverage of residents over sixty-five; (iv) coverage of the working population at their place of work (**Table 1**). All variables are based on data from the 2011 Census, available at the Output Area (OA), an administrative unit representing on average 125 households (ONS 2011). It is common to use population data mapped on to a 1 km square grid. By using OAs instead, we retain data at much higher granularity, with a median area around twenty times smaller than this (0.05 km²). However, OAs in sparsely populated areas on the outskirts of the city can be much larger, with 10 of the 910 OA in Newcastle having an area greater than 1 km².

We use a count of the population in each OA, rather than a proportion, to reflect the number of people in each demographic covered by a potential sensor. In the analysis that follows, these demographic variables shape the spatial optimisation process, and the sensor networks that emerge. **Figure 2** provides an illustration of the relative importance of different variables across Newcastle, based on the overall coverage provided by placing a sensor in this OA (using a 500-metre solution). To calculate sensor coverage based on these demographic variables we consider an OA to have 100 percent coverage if it contains a sensor. In those OA without a sensor, coverage is based on the distance to the nearest OA with a sensor (Equation 1). We place sensors at, and calculate coverage based on the distance between, the population-weighted centroid of each OA (Office for National Statistics 2011). This allows us to better capture the distribution of people within an OA compared to using their geographical centres.

In our single-objective greedy optimisation we seek to find the network of sensors j that maximises total coverage of the city for a specific variable, as defined by:

$$\max_j \frac{\sum_i n_i c_{ij}}{\sum_i n_i} \quad 2$$

Where n_i is the number of people in output area i for the variable of interest (the number of children under sixteen resident in that OA, for example). In other words, we maximise the weighted average of the coverage across all OA, considering the demographic population of each OA. In the multi-objective genetic algorithm, we calculate the overall coverage of each variable in the same way but search for promising compromise solutions between all four variables (Section 5.2).

It is important to note that several important demographic variables are not considered within the analysis. Newcastle is a diverse city with 13.4 percent of its population born outside the UK (Newcastle City Council 2021). Furthermore, there are significant areas of deprivation within the city, with 23 percent of people in Newcastle living in the 10 percent most deprived areas nationally. Environmental justice research evidences how structural forms of inequality and discrimination mean that these populations are likely to be more exposed to pollution and other urban ills, making them a priority for sensor placement. Our analysis is intended as an illustration of the importance of incorporating demographic factors into the sensor placement decision-making process, and not as a statement on the universe of potential input variables that should be considered. In addition, age data are easily obtained for very small geographic areas of the UK and so offer the most tractable demographic data for our purposes.

Table 1. Demographic variables at OA scale.

Variable	Description	Justification
Total Residents	Total residential population in the OA	Providing coverage to as much of the total residential population as possible, with all population members considered equally. Likely prioritising denser, highly populated areas.
Residents under 16	Number of children under the age of 16 years	Prioritising coverage for young persons who are physiologically vulnerable to poor air quality.
Residents over 65	Number of persons aged over 65 years	Prioritising coverage for older persons who are physiologically vulnerable to poor air quality.
Workers	Number of persons with place of work in the OA	Providing coverage to as much of the total population as possible, based on their location during the working day. Likely prioritising commercial and industrial urban areas. The workplace population includes home workers and resident workers with no fixed place of work, and non-resident commuters into the area from anywhere in England and Wales (Bradley 2014).

[1] In the analysis demographic data granularity is restricted to Census OA. This has implications for the 100-metre solution in particular, as we are not necessarily calculating coverage within 100 metres owing to the relatively larger size of the OA. Rather the results indicate whether a sensor covers the immediate OA it is within, without benefiting any of the surrounding OAs. It is also worth noting that whatever the value of θ an OA is considered to have coverage of 100 percent if it has a sensor.

5. Illustrating Trade-offs And Inequities In Sensor Placement Using Spatial Optimisation

Based on our spatial optimisation of sensor placement according to the demographic structure of Newcastle, the section that follows presents:

1. Single objective sensor networks derived to prioritise coverage of a single demographic variable (Section 5.1); and
2. Multi-objective sensor networks derived to prioritise a number of demographic variables (Section 5.2).

For both single and multi-objective sensor networks we also evaluate how they perform in comparison to the existing network of air quality sensors that form part of Newcastle's UO (Section 5.3.).

5.1. Single Objective Sensor Networks

Overall sensor coverage scores for each demographic variable of interest, based on a single objective network, provide a measure of the extent to which the population of interest is covered with a given number of sensors, with a score of 1 representing complete coverage. **Figure 3** shows the relationship between the number of sensors (between one and fifty-five), and sensor coverage. The number fifty-five is chosen as a benchmark for analysis to allow for comparison with the existing UO network of air quality sensors, which provides sensor coverage in fifty-five OAs in Newcastle.

For the workplace population, a small number of sensors can provide coverage of a high proportion of the population. For example, the placement of a single sensor provides coverage for 16 percent of the workplace population, rising to 22 percent coverage using two sensors. These high sensor coverage scores reflect the spatial concentration of the workplace population in the dense city centre and the city airport, in comparison to other demographic variables that are more evenly distributed across Newcastle (**Figure 1**). The remaining three variables (total residents, residents under sixteen, and residents over sixty-five) each have a similar relationship between coverage and the number of sensors. Subsequently, a high degree of sensor coverage amongst these populations is less straightforward to achieve compared to the workplace population. For example, when comparing the total resident population (i.e., whether a person is covered at home) to the workplace population (i.e., whether a person is covered in their place of work), using twenty-five sensors only 39 percent of the residential population has coverage in comparison to 62 percent of the workplace population using the same number of sensors.

Workplace populations represent an opportunity for urban decision-makers to provide coverage to a large proportion of the population during the day, using only a small number of sensors. Workplaces are also likely to be located in denser, and relatively polluted, areas of cities given the high volume of people travelling to city centres or other major centres of industrial activity. However, focusing on workplace population means that data is less likely to be collected about a range of demographic groups who are not in paid employment. This includes, for example, people who are retired or carers, including parents looking after children at home (Carr et al. 2018), as well as people who are structurally disadvantaged in the job market, including women (Hebson and Rubery 2018), ethnic minorities (Longhi 2020), and persons with poor physical or mental health that means they are unable to work or their employment opportunities are restricted (Maroto and Pettinichio 2014). Arguably, many of these demographics are disproportionately vulnerable to poor air quality, for both physiological and structural reasons, meaning that they require greater (not less) representation in efforts to understand inequalities in the urban environment (Kempin Reuter 2019; Heeks and Shekar 2019).

Comparison of sensor coverage across the three residential demographic variables using a 500-metre solution, based on the number of sensors (**Figure 3**) also highlights the relative gains in terms of coverage that can be made via the placement of a small number of sensors across each variable. In Newcastle, a medium-sized city in the UK context, the placement of ten sensors using a 500-metre solution provides between 22–25 percent coverage in those networks optimised for the single objectives. Yet the addition of a further forty-five sensors results in a network that provides just over twice the level of coverage (53–55 percent) in each case. However, it is important to note that these results are highly context specific and will likely vary depending on a number of factors, not least the size, density and diversity of the urban environment and populations that a sensor network seeks to represent.

Focusing in detail on the spatialities of the single objective networks, in which sensor coverage is based on a specific demographic group, the configuration of sensors based on residents over sixty-five is more challenging from a coverage perspective. As illustrated in **Figure 4**, older persons are the most geographically dispersed of the populations selected for analysis. As sensor coverage is based on distance (in our case a 100 metre or 500 metre solution) the tendency for older persons to live in less dense, suburban areas of Newcastle means that a large number of sensors are likely to be required to achieve similar levels of coverage. This reflects long-standing challenges associated with understanding, tackling and targeting some of the challenges in rural areas in the UK (e.g. poverty and social exclusion), due to both their relative peripheralisation and diversity compared to their urban counterparts (Commins 2004; Walker et al. 2012). For example, the 100 metre solution using ten sensors only provides coverage to 4 percent of older persons, compared to the 34 percent coverage achieved for a network configured in the same way based on the workplace population variable (**Figure 5**). Despite this, a fifty-five sensor network for a 500 metre solution based on residents over sixty-five (53 percent) achieves similar levels of coverage to the deployment of the same number of sensors based on total residents and children under sixteen (53 percent and 55 percent respectively).

Each of these spatially optimised networks are limited as they only account for a single variable of interest. Whilst in some cases evidence from sensor networks might be used to inform policies pertaining to a single group (e.g. when considering the physiological vulnerability of a particular age group to poor air quality), it is often useful for urban decision-makers to consider populations more holistically—concurrently representing the needs of a wider range of demographic groups. The following section seeks to address this, focusing on deriving multi-objective sensor networks.

5.2. Multiple Objective Sensor Networks

We begin by configuring a network that seeks to balance the importance of two demographic variables with the least similar spatial distribution: workplace population and residents over the age of sixty-five (**Figure 6**). As we move from the sensor network that provides maximal coverage based on older persons (top left) to the network that provides maximal workplace coverage (bottom right) we see a shift in the spatial distribution of sensors towards the city centre. It is worth noting the substantial gains in workplace coverage that can be made with a relatively small change in the degree of coverage of older persons, owing to the spatial concentration of working populations during the day. For a network of 55 sensors, an 8 percentage point reduction in coverage of the residents over sixty-five (from 51 percent to 43 percent) results in a 37 percentage point increase in coverage of workplace population.

It is also possible to evaluate a range of networks optimised based on all four demographic objectives. As we add additional objectives into the optimisation, a greater combination of networks emerge that vary depending on which populations are prioritised over others. **Figure 7** shows the degree of coverage achieved for each objective according to 200 different multi-objective sensor networks^[2], each based on a 500-metre solution. 45 percent coverage is used as a bench-mark (indicated by the horizontal line), and those networks with at least 45 percent coverage of all four objectives are shaded in blue. Of the 200 networks, 92 networks meet these criteria. The sensor coverage achieved by the networks demonstrate just how tricky evaluating sensor placement based on multiple objectives can be. None of the networks achieve over 50 percent coverage of the population across all four objectives using 55 sensors (eight have between 49 and 50 percent coverage). As the overall coverage of the city depends on the assumed sensor coverage area, a 100-metre solution would need many more sensors to meet the 45 percent threshold for all objectives.

5.3 Comparison with the Existing Urban Observatory Network

The existing UO sensor network in Newcastle was not necessarily designed with demographic coverage in mind; rather it is intended to respond to specific urban challenges and policy priorities. As a result, the 146 air quality sensors in Newcastle that form part of the UO network are disproportionately concentrated in the city centre (**Figure 8**).

Figure 10 compares the existing UO network and each of the single objective sensor networks derived solely based on the spatial distribution of population. To calculate the degree of sensor coverage based on the existing UO network, we snap each UO sensor to the centroid of the OA it falls within, resulting in 55 OAs with sensors. Coverage is then calculated using the same method as our spatial optimisation (Section 4.2). Orange areas illustrate where the existing UO network provides less coverage (or a deficit of coverage) and purple areas indicate where it provides more coverage (or an excess of coverage), when compared with the single objective networks.

The spatial distribution of the existing UO network is most closely aligned with the distribution of sensors based on the network optimised for workplace population (illustrated by a higher number of white areas in which coverage difference is zero) (**Figure 10**). However, there are areas for which existing sensor coverage is sparse, including relatively deprived, post-industrialised areas along the north bank of the River Tyne—what might be termed sensor deserts in the existing network (Robinson and Franklin 2020). Yet the UO network provides a higher level of coverage in the centre of

the city, where people across all demographics are likely to congregate and spend much of their time, when compared with each single objective network. By prioritising residential demographics and populations, our sensor networks impose a more dispersed allocation of sensors across the urban fabric, which might be a useful outcome—a nudge to decision makers to consider a wider range of areas in placing sensors.

Figure 10 evaluates sensor coverage for 200 multi-objective networks each comprised of 55 sensors (Section 5.2). All 200 networks have a corresponding marker within the four groups of points in the swarm plot, whilst the horizontal line represents the level of coverage achieved using the existing UO sensor network (one sensor to represent each of the OA that contain a sensor). The shading of each point tells us how a sensor network performs according to the four demographic objectives. Networks shaded blue have better coverage than the UO network across all four objectives; those shaded pink have worse workplace coverage than the UO network, although coverage is better than the UO network across the remaining three objectives.

For three of the objectives—total residents, residents over 65, and residents under 16—all 200 of the spatially optimised sensor networks provide a higher degree of sensor coverage than the existing UO network. However, to achieve the coverage of workplace populations that matches the existing network in Newcastle it is necessary to sacrifice some degree of coverage across the remaining three objectives, as illustrated by the band of points shaded in pink clustering at the top of the swarm for the total residents, residents over 65, and residents under 16 variables. These networks have poorer workplace coverage than the UO network, but perform better across all other objectives.

Comparison with the UO air quality sensor network highlights some of the limitations of the networks derived via spatial optimisation. The spatial optimisation only accounts for the distribution of the population, overlooking other aspects that decision-makers may choose to prioritise to understand urban air quality—for example, sources of pollutants and relative exposure to pollutants. We are also unable to consider the practicalities of where sensors can be safely and effectively installed, a decision-making process that can be highly contested and political, thus shaping the distribution of the existing network. Furthermore, the analysis is limited by the OA boundaries in which demographic data is made available. For example, within the UO network there are areas in the city centre in which air quality sensors are so densely located that they are not easily comparable with the lower granularity networks derived using a 500 metre spatially-optimised solution. Finally, the optimised demographic sensor networks consider the population as relatively immobile rather than ambient (Whipp et al. 2021), with the exception of some representation of the “daytime” configuration of a city’s residents, via the workplace population variable. Optimisation of sensor placement should also prioritise understanding the coverage of the population as they travel within the city, whether to work, school or other activities, rather than solely focusing on their home location (as is prioritised by data available from the Census).

[2] 200 was selected as an appropriate number of sensor networks that was computable within a reasonable analysis time but also allowed for a full spectrum of possible compromises to be generate.

6. Reimagining The Role Of Sensors In Cities

Even when evaluating a limited number of (primarily demographic) priorities in our evaluation of the placement of air quality sensors in cities, the analysis presented suggests that there is no such thing as “optimal” coverage within the constraints of existing urban structures—or that achieving such a goal lies so far outside the realm of possibility that we can consider it impossible, given existing technologies. Our results suggest that, even with access to appropriate information and analytics, urban decision-makers may struggle to develop equitable solutions, where sensor networks are concerned. We view this as a peculiarly spatial instantiation of injustice in the smart city. These results also suggest that inequities in sensor networks need not be the outcome of unfair, unjust, or biased processes—even with “optimal” decision-making, sensor networks are likely to miss important groups or locations. Notwithstanding the impacts of austerity policymaking on local government capacity for monitoring in recent decades (Eckersley and Tobin 2019), in the absence of an unlimited budget for sensor placement and maintenance, our analysis suggests that sufficient sensor coverage that would allow for the collation of reliable and accurate real-time data across all groups and places in the city is likely an almost impossible task.

Despite this, we would argue that the “just good enough” (Gabrys et al. 2016) or “satisficing” (Herbert 1955) data has the *potential* to play an important role in evidencing core urban injustices such as air pollution and climate-related heat, if data are collected with equity in mind. We therefore make the case for a clearer distinction to be made within critical debates about smart urbanisms between sensors for monitoring and sensors for surveillance, arguing that a wider presumption of bad intent for all sensors potentially limits the visibility of positive types of sensing—and may also limit uptake of existing analytical approaches, such as spatial optimisation, that can support decision-makers in understanding the spatial and demographic impacts of trade-offs, as they are made.

Rather than starting from what we think we already know about the city and working from there in the placement of sensors, the approach presented within this paper allows us to evaluate and compare a variety of sensor configurations that have equity at their core. The networks developed are by no means perfect, limited in the lack of recognition of known sources of hazards, the range of demographic characteristics considered, or how people move in and out of sensor coverage within the city. Yet the widely used and replicable spatial optimisation algorithms applied in our analysis allow for the construction of networks that offer a different perspective about who or what urban sensor infrastructures are for. In turn, those sensors are likely to generate data that we did not anticipate. Such an approach has the potential to provide a more holistic understanding of the city, rather than

beginning with preconceived ideas about what is important to measure, or retrospectively evaluating whether an existing network is equitable or not. They also succeed in making visible the spatial and demographic implications of a core element of smart city technologies: the sensor

That is not to argue, as we build these networks, that sensors are the panacea that proponents of smart cities and big data might claim. Instead our analysis highlights the ways in which basic optimisation tools can helpfully elucidate spatial inequalities, recognising how optimisation visualisations and tools can be a useful mechanism for communicating to decision-makers and citizens just how difficult the challenge of equitable sensor placement is. In successfully conveying these difficulties, the analyses could act as a catalyst for important broader conversations about whether there are better alternatives to sensors for gathering data that helps people. Given the challenges associated with sensors (whether for surveillance or monitoring purposes) it is useful to consider what we might do instead. Perhaps there are alternatives for collecting necessary information that do not invade privacy, or risk privileging some places or people over others, that would allow us to reimagine the role of sensor infrastructures in our cities.

Declarations

Data Availability Statement

All code and source data for our analysis is available in the GitHub repository: [omitted for blind peer review]

Competing interests: The authors declare no competing interests.

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Figures

Figure 1

Density of demographic variables across Newcastle. Distribution of each variable, all on the same scale using a density calculated as % of people in the OA, divided by the area of the OA. Data source: Map tiles by Stamen Design, under CC BY 3.0. Data by OpenStreetMap, under ODbL. Office for National Statistics licensed under the Open Government Licence v.3.0. Contains OS data © Crown copyright and database right 2021.

Figure 2

Distribution of demographic variables across Newcastle based on importance. Importance is the overall coverage provided by placing a sensor in an OA (using a 500-metre solution).

Figure 3

Sensor coverage score based on number of sensors for demographic variables (using a 500-metre solution).

Figure 4

Coverage of residents over 65 based on ten and fifty-five sensor networks using 100 metre (left) and 500 metre (right) solutions.

Figure 5

Coverage of workplace population based on ten and fifty-five sensor networks using 100 metre (left) and 500 metre (right) solutions.

Figure 6

A two-objective 55 sensor network showing the trade-off between residents over 65 years and workplace population. Network varies from maximal older person coverage (top left) to maximal workplace coverage (bottom right).

Figure 7

Sensor coverage for multi-objective, 55 sensor networks ($n = 200$) based on a 500-metre solution. Networks coloured blue have at least 45 percent coverage across all four objectives.

Figure 8

Existing air quality sensors in the UO network within Newcastle LA. Data source: Sensor locations derived from Urban Observatory at Newcastle University under CC BY 4.0, <https://urbanobservatory.ac.uk/>

Figure 9

Difference between existing UO network of air quality sensors and single objective networks derived for each demographic variable.

Figure 10

Difference between existing UO network of air quality sensors and multi-objective 55 sensor networks ($n = 200$). The horizontal line shows the coverage of the existing UO network for each objective. Networks shaded blue have better coverage than the UO network across all four objectives. Networks shaded pink have worse workplace coverage than the UO network but better coverage than the UO network across the remaining three objectives.