GEO-ANALYTICS OF CITIZEN-GOVERNMENT INTERACTION: THE INTEGRATION OF SPATIAL DATA MINING, VOLUNTEERED GEOGRAPHIC INFORMATION (VGI), AND GEOVISUALIZATION TO EXPLORE NON-EMERGENCY REQUESTS IN THE STATE OF KUWAIT

by

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DEDICATION

I dedicate this dissertation to my dear parents for their endless support throughout my life. Their care and kindness to me was, and still, motivating me to be a better person:

"*Thy Lord hath decreed that ye worship none but Him, and that ye be kind to parents. Whether one or both of them attain old age in thy life, say not to them a word of contempt, nor repel them, but address them in terms of honour. And, out of kindness, lower to them the wing of humility, and say: "My Lord! bestow on them thy Mercy even as they cherished me in childhood*."" (17:23,24)

To my dear wife who stood by my side since the first day I met her. The patience and compassion I received from her derived me to complete this journey. Thank you.

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To my brothers and sisters. Thank you.

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ABSTRACT

The rapid and continuous growth of population requires simultaneous provision of public services (or commons) at high spatial and temporal scales. In addition to the commons provision, governments are ought to maintain the commons to be at high quality standards. However, the rapid consumption of the urban commons, with the urban expansion in space, represented a challenge to local governments to sustain the provided services. Consequently, low quality services are expected to be detected by the community. Building on the sense of owning the space, or territoriality, citizens are interacting with local governments to report about the low-quality commons. In response, governments have established a centralized system for such reports, or non-emergency requests, and it was initiated by the U.S. government in 1996 known as the 311 system. Such centrality facilitated the process to report a complaint with no need of prior knowledge on whom and how to submit the complaint. However, such system does not exist globally and in such cases, citizens should obtain prior knowledge on whom they should contact to submit a complaint. An example would be the State of Kuwait.

In Kuwait, citizen complaints are received by the responsible agencies individually. Building on the territoriality theory, a group of volunteers leveraged the use of Social Media (SM) technologies to establish a centralized point of communication for Kuwait users to share their complaints with responsible agencies. Through their SM account, known as @Q8needsyou in Instagram, citizen complaints could be collected,

organized, processed, and analysed to explore the spatiotemporal nature of the citizen-government interaction in Kuwait, which represents a contribution to the body of knowledge in such part of the world. The overall objectives of this dissertation where to: 1) design a structured relational database for citizen complaints, 2) identify the spatiotemporal cluster of citizen complaints at the global and temporal level, 3) identify the socioeconomic characteristics that influence the complaints volume and governmental responsiveness to complaints, and 4) explore the agencies interconnectivity nature through geovisualization. The data collected covered the year 2019.

In Chapter 4, the results of the spatiotemporal pattern analysis revealed several insights. The global pattern analysis results using Averaged Nearest Neighbor (ANN) have shown that complaints exhibited a clustered pattern during 2019 and during each season. Also, the same pattern was found when analyzing the top two complaint types. The results of the local pattern analysis using the Getis Ord, or Gi*, statistics at the neighborhood level revealed several findings. It was found that there are areas that exhibited high clusters of citizen complaints during 2019, and the high clusters vary spatially during each season. The same findings were identified when applying the analysis for the top two complaint types.

In Chapter 5, Factor Analysis (FA) and Multiple Regression (MR) were implemented to identify the significant socioeconomic factors that contributes to citizen complaints volume and governmental responsiveness (rate and response time). The findings, regarding complaints volume, were consistent with the literature where higher married population and higher education level tends to have more propensity to submit complaints. Regarding governmental responsiveness, factors such as population density, education level, and male population had a significant positive influence on responsiveness rate and time.

Finally, in Chapter 6 bivariate mapping methods have shown that gender digital participation exhibited spatial variation in 2019 and during each season. Also, the multivariate mapping approach revealed multiple insights were citizen-government interaction had varying patterns at the neighborhood level. Finally, using geovisualization to explore the agency interconnectivity revealed that connections among agencies, and the magnitude of the connection, varies at the governorate level.

Building on the findings of this dissertation, the necessity to establish a centralized system for citizen complaints gain its importance through time. The system should rely on the traditional (or authoritative) and digital media sources of requests to leverage the awareness on where and when to maintain the urban commons.

1. INTRODUCTION

Governments around the world seek to provide public goods and services (e.g., healthcare, transportation systems, environmental protection, industrial and commercial activities, and local/national security) that are efficient, equitable, and enhance their citizens' quality of life. However, achieving these objectives is increasingly complicated by population growth and rapid urbanization (Singleton, Spielman, and Folch 2017). For instance, providing "government goods" (Minkoff 2016) requires continuous monitoring to meet local needs at a high quality; yet, both provision and monitoring are costly activities that become exceedingly difficult and more expensive to manage as the number of constituents receiving those goods—and the spatial footprint in which goods are provided—increases (Schwester, Carrizales, and Holzer 2009). Partially due to the mismatched growth rates in population and governmental capacity, with the former occurring faster than the latter, governments are often accused of being inefficient and ineffective when it comes to providing public goods and services (King and Nank 2011).

To put the problem in context, consider that global patterns of urbanization and economic development are intensifying at alarming rates. The global population is projected to grow to 9.7 billion persons by 2050 (United Nations 2015), and more than half of the world's population already lives within urban areas—including numerous fast-growing megacities of ten million or more residents. With these sorts of figures and trends in mind, it is reasonable to assume that in the not-too-distant future, public sector services will become even more difficult and expensive to (1) provide to rapidly growing residential and commercial populations, (2) retain standards of quality, and (3) monitor the distribution and equitability of service provision (Singleton, Spielman, and Folch 2017).

With respect to the latter two points, it is probable that low quality and/or inequitably distributed public sector services will give rise to dissatisfied subsets of citizens who, in turn, communicate their dissatisfaction to representatives of the provisioning government unit. The spatial footprints of these resident-initiated complaints relate to the geographic concept of *territoriality*, which represents all attitudes, cognitions, and behaviors that arise from a sense of ownership of an object or space (Altman 1970; Edney 1974; Brown 1987, 2009; Taylor 1988). Territoriality and its associated sense of ownership over space explain why citizens invest time and energy in maintaining spaces to which they hold no legal title (O'Brien 2016a). As O'Brien (2016a) describes, many spaces function as "urban commons" in which people experience public space and infrastructure collectively, and those experiences shape and influence local quality of life. As such, residents—especially local citizens who encounter the urban commons on a day-to-day basis—are regularly moved to take action when the [lack of] upkeep of the urban commons negatively affects their quality of life (O'Brien 2016a). In many instances, the action taken involves reporting issues to appropriate agencies of local government. Hence, maintaining the urban commons becomes an ongoing process and collaboration between local governments and communities (O'Brien 2016a). These feedback effects, or *citizen-government interactions*, make communities a valuable source of governmental goods quality monitoring (Minkoff 2016).

As expanded on below, many places, particularly within the U.S., have been working to strengthen citizen-government interactions and increase government responsiveness to resident complaints through the use of technology and centralized reporting systems (Wimmer and Tambouris 2002; Irani, Al-Sebie, and Elliman 2006; Schwester, Carrizales, and Holzer 2009). Perhaps the best known example is the American 311 call system, which allows residents to dial a single, memorable telephone number to report any type of non-emergency issue of public concern (Weaver 2019). The complaint is then routed to the appropriate agency, which take necessary actions to address the issue—all while keeping the complainant in the loop by way of a trackable service number. The 311 call center tends to be accompanied by supporting web infrastructure—including a web-based application and smart phone application—that allows residents to submit 311 complaints electronically rather than through a telephone call (Lu and Johnson 2016; Minkoff 2016; Hartmann, Mainka, and Stock 2017; Kontokosta, Hong, and Korsberg 2017). Such technologies drastically decrease the costs and knowledge requirements that a resident needs to register a formal complaint with local government (i.e., it is not necessary to research which agency is responsible for a given type of issue), making it relatively easier for residents to communicate with local governing bodies. Consequently, 311-like technology systems create new pathways for citizen-government interaction.

That being said, 311 systems are not universally available. Rather, they are overwhelmingly found in larger urban areas in affluent nations. The absence of a centralized portal for communicating with local government has led some citizen groups throughout the world to take matters into their own hands, by leveraging the power of social media (SM) to act as a pathway for citizen-government interaction. This scenario is precisely the one playing out in the nation of Kuwait. Aside from an emergency hotline

(112), there is no "311-like" centralized service for residents to call to report non-emergency issues. For non-emergency requests, citizens effectively need to have prior knowledge about which agency they need to contact and whom at that agency to contact. Otherwise, they are left to solve their problems individually. As a result, citizens find it difficult and costly to communicate with the local government. Submitting a service request takes advanced research into the appropriate agency, and those research efforts offer no guarantee against contacting the wrong agency (miscommunication). With the rise of SM, some public agencies started to create a point of contact to enable individuals to submit requests through multiple SM platforms. Examples of SM platforms used by governmental agencies are Twitter, Instagram, and, more recently, WhatsApp. However, when each agency uses multiple channels of communication, it increases the complexity of the reporting process due to uncertainty regarding which channels are most frequently monitored, among other concerns.

To address this issue, a group of volunteers in Kuwait created an SM account to which they invite all citizens to share their concerns, requests, and suggestions regarding non-emergency situations (the account handle is @Q8needsyou on the Instagram platform[1]). The information obtained through the SM account is then shared with the responsible agency to take action accordingly. Put another way, without official governmental support, community volunteers have essentially formed something a proto-311 centralized system to solve the non-centrality of the governmental workflow of receiving services request. This act of community-based *governance* is arguably a first step towards establishing an automated, centralized, *government*-sponsored service

[1] https://www.instagram.com/q8needsyou/?hl=en

requests system in Kuwait (see [Weaver et al. 2016] on the distinction between acts of government and acts of governance). Along those lines, studying how the organic, community-based SM system operates—including who uses it, for what issues, whether patterns of use are distributed evenly in space, and the extent and distribution of government responsiveness to the system—can uncover critical insights for both understanding and enhancing citizen-government interactions in Kuwait, and for informing the development of a formal, government-supported system. More generally, evaluating the voluntary SM complaint system will move the literature on technology-based citizen-government interactions beyond widely studied formal governmental arrangements like 311 in the U.S. (O'Brien 2016a), and into the informal governance spaces being created across the globe.

Statement of purpose

To overcome the complexity of citizen-government interaction in Kuwait, a nation where there is no centralized system for linking resident concerns to appropriate governmental units, volunteers created a semi-centralized point of communication to receive citizen requests for service through multiple SM platforms. Through these platforms, key (but unorganized) information about each concern is shared via SM. The information included in most submissions include time, type of complaint, location, and responsible agency for each complaint. In other words, the volunteer-run system collects and publishes volunteered geographic information (VGI). Because of the transparent nature of reporting, VGI broadcast through SM offers a dynamic look at the volume and spatial distribution of citizen complaints—and government agency responses to those complaints—in real time. By contrast, traditional modes of citizen-government communication in Kuwait rely on direct agency contact (e.g., via telephone or face-to-face) that tend to be slower and costlier than SM (insofar as residents need to know which agency to contact about their concern).

With that in mind, the purpose of this dissertation is to map and investigate the geographies of resident complaints, as well as government responsiveness to those complaints, in Kuwait, using VGI-generated data from SM. By georeferencing complaints and quantifying the volume of complaints made through SM, the research reveals spatiotemporal patterns of use (in some ways, a measure of demand for) of the SM system, as well as socioeconomic characteristics that contribute to both complaint cases and governmental responsiveness to complaints across the nation of Kuwait. The findings contribute to knowledge on VGI's potential to increase and enhance citizen-government interaction in nations like Kuwait, where research on the phenomena is scarce due to lack of formal, government-sponsored systems like 311 in the U.S. The findings show that there is demand for a centralized "311-like" system in Kuwait, and they suggest that the rapid world of SM and other web-based technologies can improve government service delivery in urbanizing jurisdictions. The specific objectives of the dissertation were to:

1- Design and implement a structured relational database for community complaints from VGI.
2- Explore the spatiotemporal patterns of VGI-generated complaints for evidence of spatiotemporal clustering at global and local-levels.

3- Compare the socioeconomic and demographic characteristics that drive the volume of complaints and propensity of public sector responses to VGI-generated complaints.

4- Implement geovisualization methods to explore citizen-government interaction indicators and agency interconnectivity based on VGI-generated complaints.

To facilitate those objectives, the dissertation tested the following null hypotheses (broken out by Chapter):

- **Chapter 4:**
    - **$H_{0,1}$:** The point distribution of complaints is random.
    - **$H_{0,2}$:** Complaint rates are randomly distributed across all residential neighborhoods.
- **Chapter 5:**
    - **$H_{0,1}$:** Neighborhood-level complaint volume does not vary systematically by neighbourhood socioeconomic or demographic conditions.
    - **$H_{0,2}$:** Government responsiveness to citizen complaints does not vary systematically by neighborhood socioeconomic or demographic conditions.
    - **$H_{0,3}$:** Government response time to citizen complaints does not vary systematically by neighborhood socioeconomic or demographic conditions.

After these hypotheses are tested and the findings are situated in the scholarly literature, Chapter 6 carries out two additional applied research objectives aimed at visualizing the data for public consumption by residents and governmental officials in Kuwait:

- **Objective$_1$**: Implement multivariate mapping methods to identify spatial clusters of citizen-government interaction characteristics at the neighborhood level.
- **Objective$_2$**: Implement geovisualization methods for agency interconnectivity at the country and governorate level.

A final chapter (Chapter 7) briefly summarizes the dissertation's main contributions and opportunities for future research.

2. LITERATURE REVIEW

The research contained in this dissertation is informed by four principal, overlapping themes and literature streams: (1) territoriality, co-production, and Citizen Relationship Management (CRM), (2) non-emergency citizen request systems (hereafter 311), (3) Volunteered Geographic Information (VGI), and (4) geographic research on 311 systems in the western literature. This chapter introduces readers to the fundamental concept of citizen-government interaction through the intersecting lenses of these four themes. In doing so, the chapter highlights the background, structure, and main characteristics of 311 systems and their role in citizen-government interaction. From there, historical context, features, and main implementations of VGI are presented. Finally, empirical studies that draw on geospatial knowledge (e.g. GIS and geostatistics) to investigate 311 datasets are summarized alongside significant findings from this body of research. The chapter concludes by highlighting the key literature gaps to which this dissertation is directed.

Theoretical Background: Territoriality, Co-Production, and Citizen Relationship Management (CRM)

Territoriality

Recall from Chapter 1 that community collaboration to maintain the urban commons in a space reflects *territoriality*, or a sense of owning the place. This sense of ownership manifests in a community when residents become “the eyes and the ears of the city,” meaning that they identify and report issues that require the involvement of local governments (O’Brien 2016a). Based on the sense of owning the place, territoriality shapes the landscape of a neighborhood by triggering both defensive and caretaking characteristics in residents (Brown 2009). For instance, property owners may put up fences to demarcate and *defend* their territory; and they may engage in regular landscaping—as well as intermittent decorating (e.g., for holidays)—*caretaking* activities that showcase their sense of pride in ownership (Brown and Werner 1985; Werner, Peterson-Lewis, and Brown 1989; Caughy, O'Campo, and Patterson 2001). Importantly, this sort of territoriality can extend from private features to shared ones (e.g. sidewalks). This extension is reflected in, for example, management and upkeep of public spaces in one's neighborhood (Harris and Brown 1996). The "defense" component of territoriality in this broader spatial sense is most consistent with behaviors that contribute to informal social control in a given geographic area (e.g., protecting the neighborhood from violations committed by others).

In general, public issues stemming from this sort of informal social control can arise from either (1) natural deterioration and place-based interruptions to normal life that result when local features stop functioning or performing at expected levels (e.g. potholes or street light outages); or (2) incivilities perpetuated by others, or human-induced disruptions to everyday life (e.g. graffiti or abandoned vehicle) (O'Brien 2016b). In most cities, resolving either of these classes of issues is the responsibility of local government. However, to the extent that local governments lack the resources and capacities to continuously monitor all urban commons at all times, governments rely on citizens to report issues through government-provided communication channels that enable community members to play an important role in local public affairs. This process reflects the concept of *co-production*.

Co-production

The concept of co-production provides a lens through which to envision better public services and more transparent government (Pestoff, Osborne, and Brandsen 2006). Overall, co-production, which has origins in the political science literature, refers to the execution and enforcement of policy through a collaborative effort between constituents and government agencies (Whitaker 1980; Ostrom 1996). While there is no consensus on the precise definition of co-production, Gao (2018) described it as the process through which inputs are used to provide goods or services that are contributed by citizens or groups outside the government. In this sense, individuals and/or groups become active producers rather than pure consumers of public services (Linders 2012; Jakobsen and Andersen 2013). Relatedly, Loeffler and Bovaird (2016) defined co-production as public services, service users, and communities making better use of each other’s assets and resources to achieve better outcomes or more accountable public agencies. Alford (2002) identified three leading roles of people in the co-production of public goods. Namely, people tend to act either as: (1) clients who receive private benefits without necessarily contributing to production of public goods; (2) volunteers who create benefits that are realized mostly by others and not the volunteer producers; and (3) citizens who both collectively produce and collectively consume public goods.

Co-production can have both benefits and limitations. As described by Brudney and England (1983), co-production is positive, voluntary, and active in nature. Among the benefits of co-production are increasing service efficiency and quality by integrating local knowledge (Parks et al. 1981), strengthening civil society (Torres 2007), and promoting a culture of democracy and citizen engagement (Bovaird 2007). However, co-production is not infallible, as it can result in uneven patterns of public goods due to citizens' uneven access to resources and ability to partake in co-production processes (Jakobsen and Andersen 2013).

Where and when the territoriality behavior of some residents collides with infrastructure for and traditions of co-production, governments become more than service providers for residents. They are instead interactants with residents and communities – they are constantly involved in receiving, storing, processing, and sharing public services. Not surprisingly, managing all of these activities is a complex process, particularly in jurisdictions that are experiencing rapid population growth (Brudney et al. 2004; O'Brien 2016a). Consequently, governments have been increasingly embracing the rise of Web 2.0 and its advanced applications and systems that enable users to evolve from information receivers to content creators (Johnson and Sieber 2013). More specifically, many local governments throughout the world have embraced web-enabled "customer relationship management" and have developed Citizen Relationship Management (CRM) systems.

Citizen Relationship Management (CRM)

As implied above, CRM evolved from the customer relationship management systems used in the private sector to manage customer interactions and collect data to inform product and service development strategies (King 2007). Building on that foundation, local governments are adopting CRM systems to achieve more efficiency, transparency, and accountability in their production and delivery of public goods and services (Reddick 2010). According to Reddick (2010), CRM is a powerful mechanism for moving toward a more citizen-centered government.

CRM, in the public sector, is a technology-based system and strategy for meeting citizen needs and enabling citizen participation in government (Chen and Popovich 2003; Richter, Cornford, and McLoughlin 2004; Teo, Devadoss, and Pan 2006; Schellong 2008). CRM systems integrate people, technology, and business processes together as part of advanced information systems (Chen and Popovich 2003). In the public sector, CRM is increasingly seen to be a requirement for improving operational efficiency and providing enhanced customer service (Holmes 2007). Improving citizens satisfaction through enhancing government accountability and flattening the citizen-government relationship is among CRM main goals (Schellong and Langenberg 2007). Still, despite the growing perception that CRM systems are necessary to the efficiency and effectiveness of government services, several challenges can prevent such systems from being implemented. These challenges include: lack of contact channels alignment and lack of marketing or outreach to citizens on the availability of CRM systems (Reddick 2010); and, perhaps most critically, lack of access to the funds and technology needed to design, implement, monitor, and update these systems. This latter challenge is especially apparent in less densely populated settlements (e.g., rural communities), as well as in jurisdictions outside of the U.S./global North context in which much of the research on government CRM systems is currently set. To that point, both adoption of and research on CRMs in local government in the global North is on the rise, arguably due to what has become the most common form of public sector CRM: the non-emergency 311 system developed in and spreading throughout the U.S.

Non-emergency Centralized Systems (311)

In the United States, an increasingly common example of citizen-government interaction is the 311 call system service found in scores of municipalities across the country (O'Brien 2016b; Xu et al. 2017). The 311 service is a multi-channel centralized system (including an easy-to-remember telephone hotline [311], a web-based application, smartphone apps, face-to-face, and social media), provided by local governments to allow citizens to request non-emergency city services and report issues and concerns (O'Brien 2016a; Hartmann, Mainka, and Stock 2017; Zobel, Baghersad, and Zhang 2017). The 311 system began in the U.S. as an alternative hotline to process non-emergency requests in an attempt to reduce pressure on the 911 (emergency) call system. This new, non-emergency system was originated at the request of then-President Clinton in 1996 (Holzer et al. 2006). The city of Baltimore was the first in the U.S. to implement the system at a citywide scale (Schwester, Carrizales, and Holzer 2009), and the number of American cities with a 311 center reached about 300 by 2014 (Nam and Pardo 2014). Importantly, however, the growth of 311 systems has not been limited to the U.S., with 13 of 27 European Members States now using the system (Idicheria et al. 2012). In some European countries, similar systems are used, but with different call numbers—such as 11414 in Sweden, 112 in Finland, 115 in Germany, and 101 in the United Kingdom (Xu et al. 2017).

At bottom, a 311 or similar system enables automation of governmental processes and direct citizen input, which is assumed to enhance the effectiveness of public administrations (Cordelia 2007). One of the system's most user-friendly features, aside from the convenient contact number, is that citizens are not required to have prior knowledge of the responsible agency to solve their problem or answer to them. Put another way, by calling the central number, the search (or transaction) costs involved in reporting issues to local government are meaningfully reduced for citizens. The system eliminates one's need to research the appropriate reporting agency, or to become trapped in a series of phone transfers. Rather, prospective users can dial a single number and their input is routed to the appropriate location. In theory, by reducing the cost of territoriality or custodianship through the removal of search/transaction costs (O'Brien 2013), the 311 system has the potential to increase citizen participation in government (i.e., to increase the frequency and density of citizen-government interactions).

By implementing these centralized systems, governments are essentially transforming from street-level bureaucracies (the use of e-government tools for the collection and storage of information and data) to system-level bureaucracies (the evolution of fully automated electronic systems) (Paulin 2013). That development puts governments on the path to eventually reach what has been called the last stage of e-government maturity, which is the full integration of government digital services across public sectors and providing governmental information at a single point of access (i.e., a web portal) (Wimmer and Tambouris 2002; Irani, Al-Sebie, and Elliman 2006).

The upshot is that, with the rise of advanced technology (both hardware and software), communication with local governments can now be accomplished through at least two modes: (1) *traditional channels* (e.g. face-to-face, phone, or mailing); and (2) *digital media channels* (e.g. social media or mobile apps) (Hartmann, Mainka, and Stock 2017). By augmenting traditional channels with digital media channels, public sectors provide citizens with a wider array of choices, and, as such, increased opportunity, to participate in government. As citizens take advantage of those opportunities, and as technological usage and uptake spreads throughout a community, government service providers benefit from an enhanced ability to detect problems with the quality or distribution of public services or service delivery (Gulati and Williams 2013; Mergel and Bretschneider 2013; Reddick and Norris 2013). Moreover, use of digital media channels can help governments pinpoint the precise time and location of an issue (O'Brien 2016a), thereby minimizing search costs on the public provider's end when responding to the complaint. At the same time, community-generated data through 311 can illuminate issues and service needs that were not previously on a government's radar (Zobel, Baghersad, and Zhang 2017).

Apart from the practical contributions of enhancing opportunities for citizen-government interactions and creating certain efficiencies, 311 systems create numerous opportunities for geographic research. More specifically, 311 users generally volunteer information on the geographic location of their complaint or service request, and many even provide information on their own home location (O'Brien 2013, 2016a). In that sense, 311 records and data often fall in the domain of volunteered geographic information (VGI). VGI refers to geographic information that is acquired by individuals or groups through a voluntary activity (Goodchild 2007). The popularity of using VGI in research has been rising steadily as more and more data are available. For example, VGI has been used in land cover assessment (Stehman et al. 2018), transportation planning (Attard, Haklay, and Capineri 2016), and disaster management (Haworth and Bruce 2015), among many other fields.

There are multiple sources of VGI (e.g. OpenStreetMap, WikiMapia, and social media), though social media (SM) (e.g. Twitter, Facebook, and Instagram), as location-based service applications, constitutes one of the more popular sources. SM data have been used in disaster and damage assessment (Houston et al. 2015; Kryvasheyeu et al. 2016), crime analysis (Malleson and Andresen 2015), and urban planning (Campagna et al. 2015; Huang and Wong 2016). This dissertation shows that they are also promising sources of data to study citizen-government interactions—similar to 311, but arguably with the ability to research more diverse study areas. More specifically, 311 has been successfully implemented (and researched) in various locations in the United States (e.g. NYC, Houston, Chicago, Boston) (Holzer et al. 2006; O'Brien 2016a). However, outside of the United States, and outside of global North nations more generally, 311 systems are far from universally available. Thus, for researchers to study technology-driven citizen-government interactions outside of the global North, SM data offer both a feasible alternative and an untapped (or under-tapped) opportunity. The remaining chapters of this dissertation tap into this potential for the case of Kuwait. Prior to doing so, however, it is important to more fully unpack the design of 311 systems and how they connect residents to governments, governments to resident problems, and resident problems to government resolutions.

311 Operations and Components

Generally speaking, 311 centers have multiple main operations, including two communication types (inbound and outbound) and two activities (service and non-service) (Schellong 2008) (Table 2.1).

Table 2.1. 311 Centers Main Operations. Source: (Schellong 2008).

	Inbound communications (Citizen-initiated)	Outbound communications (Government-initiated)
Service activities	• Service requests	• Information provision • Service request follow-up • Citizen survey
Non-service activities	• Service status • Complaint and comment handling • Information provision • Referral	

In addition to its main operations, 311 systems are composed of three main components: technology, people, and business processes (Kavanagh 2007; Tumin and Wasserman 2008) (Figure 2.1).

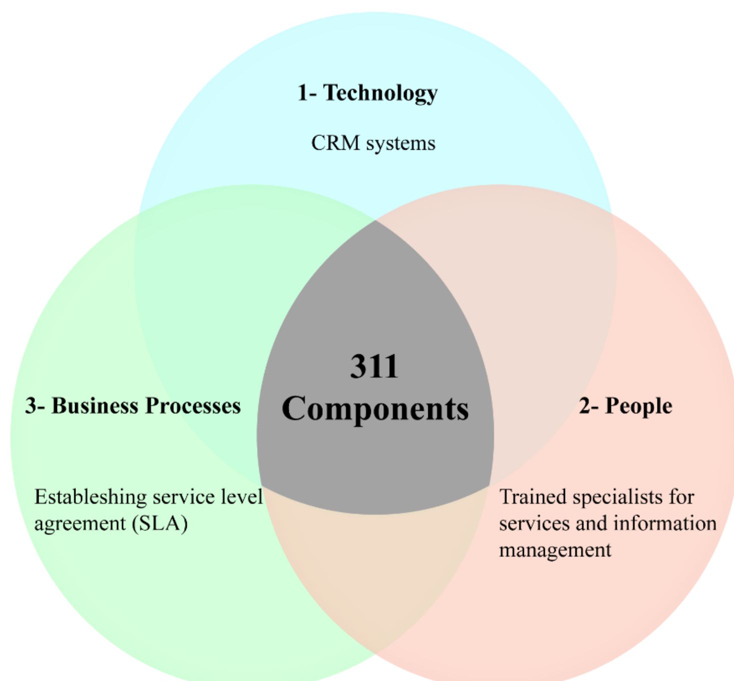


Figure 2.1. 311 Main Components. After (Kavanagh 2007; Tumin and Wasserman 2008; Nam and Pardo 2014).

The first component, technology, refers to the implementation of advanced technology to manage citizen information and, in this case CRM (in the original acronym, "C" refers to Customer) represents the technology that is central to 311 systems (Nam and Pardo 2014). Given this underpinning, it is common for the term "311/CRM" to be used in practice (Fleming 2008; Schellong 2008). The second component, people, represents trained specialists that deal with services and information requests. These specialists hold multiple titles depending on the specific application, including customer service representatives (CMRs), customer service agents (CSAs), and call center agents (CCAs) (Nam and Pardo 2014). The final 311 component, business processes, is an inter-organizational collaboration process. The collaboration with service delivery departments is essential to support CMRs to provide the most up-to-date information for the public (Nam and Pardo 2014). This process involves establishing a service-level agreement (SLA), which is "an agreement between the provider of a service and its customers which quantifies the minimum quality of service which meets the business need" (Hiles 1994). Through SLAs, city departments are committed to responding to requests within a specified timeframe (Fleming 2008). Thus, citizens will be informed when the expected work will be completed.

311 Communication Channels

Before 311 systems, citizens or city visitors were required to have a prior knowledge on whom they should contact to request a service or information (Fleming and Barnhouse 2006). The 311 approach solves this issue through the provision of a single point of contact characterized by multi-channels of communication for citizens. These channels include an easy-to-remember phone number (i.e. 311), face-to-face centers, e-mailing, online website, text messaging, phone app, and social media (Lu and Johnson 2016; Hartmann, Mainka, and Stock 2017; Zobel, Baghersad, and Zhang 2017).

The choice of channel type by citizens depend on their purpose and personal preferences. For instance, Hartmann, Mainka, and Stock (2017) assessed the channels that constitute 311 systems and whether mobile apps are more important than the other channels in New York City (NYC), Philadelphia, and Boston. They found that the preferred type of channel depends on an individual's personality, habits, and age. Furthermore, the type of request can be associated with the channel type (e.g. missed trash via phone call, even though it is possible to submit the request via mobile app, whereas graffiti removal was requested by mobile app). Phone calls were used for most complicated issues, whereas mobile app was used to send documented information, such as multimedia (Hartmann, Mainka, and Stock 2017).

311 Data Characteristics and Management

Since their launch, 311 systems have experienced a dramatic increase in the request volumes. In Chicago, for instance, the annual volume of calls received was about 3.9 million in recent years (City of Chicago 2019). The number of requests is, intuitively, a positive function of a city's population size. In NYC, for example, the number of requests has been approximately 2 million per year across a population of over 8.5 million persons. By comparison, Boston receives about 150,000 requests per year across a population of about 600,000 residents (Wang et al. 2017). The variation in the volume may be subject to sudden or unusual spikes attributed to unexpected events (Xu et al. 2017). For example, NYC311 received ~240,000 calls on December 20th, 2015, which was the first day of the transit strikes in NYC (Xu et al. 2017).

With the increase of 311 request volumes, it becomes increasingly necessary to maintain and manage the data for future use, given that not all calls can be addressed immediately. Therefore, 311 centers organize the requests they receive in structured data formats based on specific main attributes. Table 2.2 contains an example of 311 attributes from NYC311. Despite the need to standardize the 311 data, there is no agreement on such standardization of the data which leads to complexity in future integration between 311 systems among different cities (Wang et al. 2017). For example, there were 182 complaint types in NYC311, while there were only 12 types in Chicago in 2015 (Wang et al. 2017).

Table 2.2. 311 Request Attributes. An example of NYC311. Source: (Zobel, Baghersad, and Zhang 2017).

Attribute name	**Description**
Created Date	Date and time the record was created
Closed date	Date and time the record was closed
Agency name	Specific agency name
Complaint type	Category of complaint type
Descriptor	Detailed description of complaint
Incident zip	Zip code of incident location
Incident address	Street address of incident location
City	City of incident location
Borough	Borough of incident location
Due date	Date and time the request is due
Latitude	Latitude of incident location
Longitude	Longitude of incident location

Complaint types can be associated with either (1) provision, performance, and status place-based governmental goods (e.g. streets, trees, water, or lightings); or (2) negative externalities created by human actions, such as graffiti or noncommercial noise (Minkoff 2016). As an example, in NYC, the top 10 types of complaints in 2012 included heating, noise – residential, general construction, street light conditions, plumbing, paint – plaster, street condition, non-construction, water systems, and blocked driveway (Zobel, Baghersad, and Zhang 2017).

As the volume and structure of requests increase, 311 data are becoming a favorite topic in the domain of big data – an area of scholarship that has exploded in recent years. Big data differs from traditional datasets in several fundamental ways (Ibrahim and Shafiq 2017). The definition of big data remains an issue in the literature. Different studies have defined big data based on specific thresholds, such as the ability to be manipulated by conventional tools (Corea 2019). More recently, multiple studies have defined big data as data that display features of high variety, velocity, and volume (or the three V's) (Laney 2001; McAfee et al. 2012; Marr 2015; IBM 2018). However, to Corea (2019) the concept of big data refers to: "an innovative approach that consists of different technologies and processes to extract worthy insights from low-value data that do not fit, for any reason, the conventional database systems" (Dumbill 2013; De Mauro, Greco, and Grimaldi 2015; Corea 2016). Among the applications of big data concepts are governmental projects and public goods (Kim, Trimi, and Chung 2014; Morabito 2015). Since 311 data are structured big data (columns with specific types including strings and numbers), they can be stored and queried using the Structured Query Language (SQL) (Ibrahim and Shafiq 2017). Grover (2015) used SQL query functions such as join, group-by, and union to analyze a large-scale dataset. By using proper indexes for the selected columns, the data retrieval was enhanced. Similarly, Nossov, Ernst, and Chupis (2016) suggested using indexes to speed-up data retrieval and reduce the load on the memory.

To summarize, then, 311 systems are a growing topic in research on citizen-government interactions and big data. From the citizen side, 311 systems facilitate place ownership and territoriality. From the government side, they have been developed over time to utilize advanced technology to receive citizen correspondence in a structured fashion via a single point of access with multi-channels of communication. The overall conceptual flow of the requests is illustrated in Figure 2.2. The process starts with submitting requests or asking for information through one of the multi-channels of communication. The requests are received by the 311 center and stored in a structured and organized database with the specific attributes (e.g., date, type, latitude and longitude, etc.). Then, 311 specialists forward the request to the specified or responsible agency (could be submitted to multiple associated agencies). The agencies are interconnected in cases of shared responsibility (e.g. a request that requires taking action from both Water Authority and Sewer Authority). Once received, the agency forms a working staff of specialists to fix the issue. The working progress is directly under coordination with the 311 center to update the database and the status of requests. For transparency, citizens are updated at all status changes and can access the 311 system to follow the working progress and find the current status of their requests.

Since one of the main components of a 311 request is location (i.e., where an issue exists, in terms of latitude and longitude or any other form such as zip code or address), 311 requests fall within the domain of VGI. The next section expands on VGI, briefly looking at its emergence and development in geographic scholarship and engaging with its relevance to government operations and social media (SM) interactions.

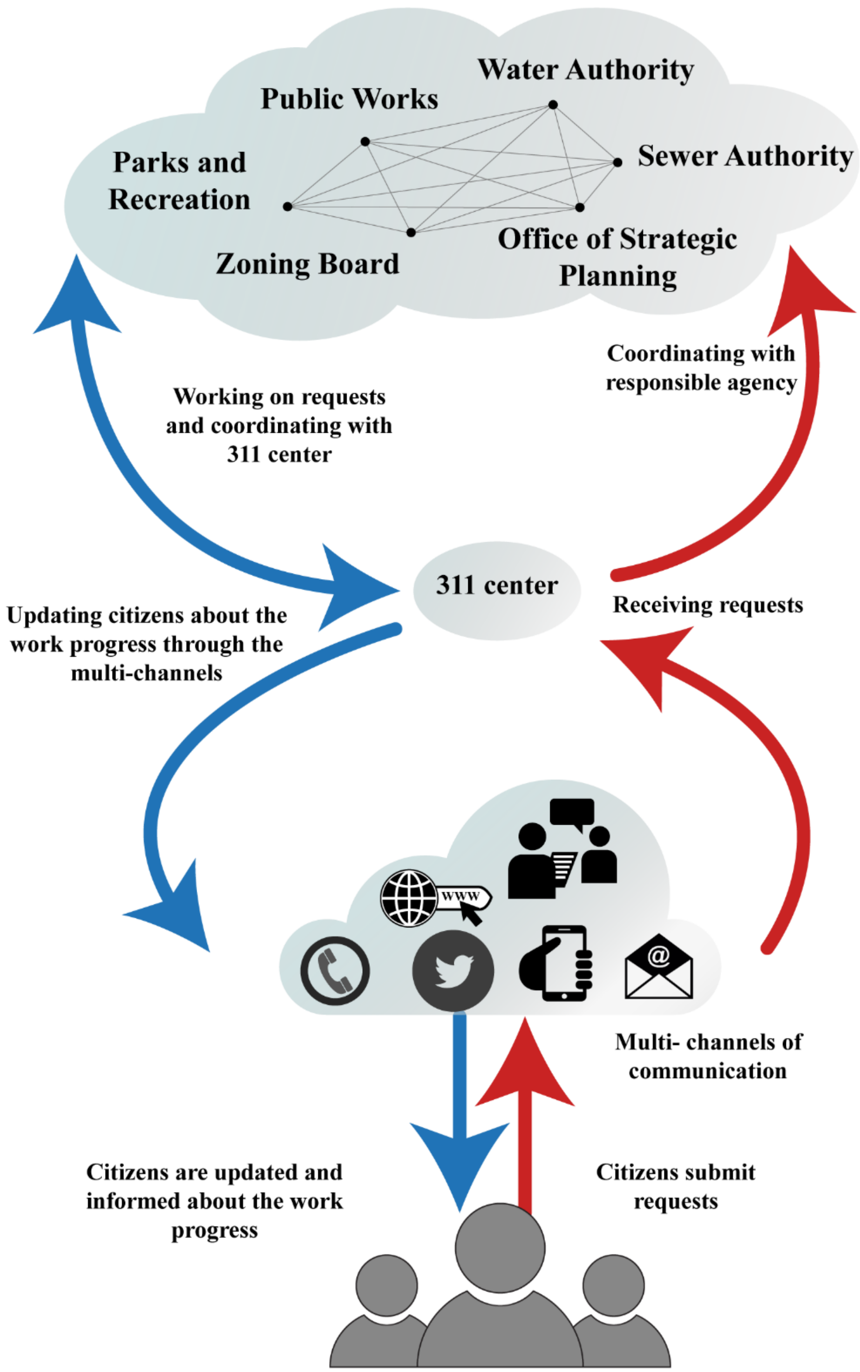


Figure 2.2. 311 Requests Overall Conceptual Flow.

Volunteered Geographic Information (VGI)

The term VGI, coined by Goodchild in 2007, can be defined as geographic information that was acquired through a voluntary activity of individuals or groups and made available for others, with the intent of providing information about the geographic world (Goodchild 2007; Elwood, Goodchild, and Sui 2012). VGI research has taken off over time and is becoming increasingly interdisciplinary. According to Scopus (2019), the US was the top country in VGI research between 2007 and 2020, with 280 identifiable studies. The top 10 countries for VGI research during that interval wee located in North America (the US and Canada), Europe (Germany, UK, Italy, Austria, and Ireland), Asia (China), and Australia (Figure 2.3). More than 980 VGI studies during that interval were published in social and computer science outlets, while another 600 were included in environmental and earth and planetary science journals (Figure 2.4).

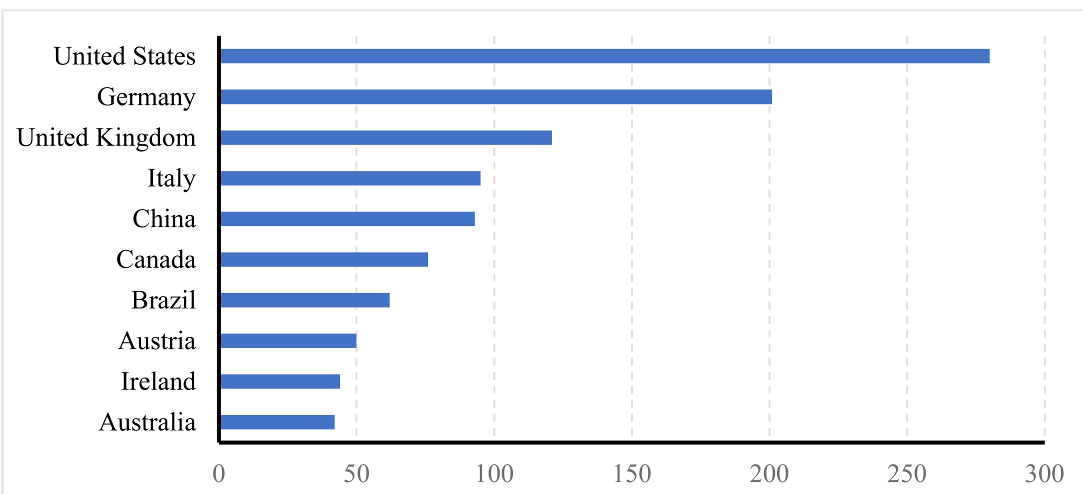


Figure 2.3. Top 10 Countries in VGI Research Between 2007-2020. Source:(Scopus 2019).

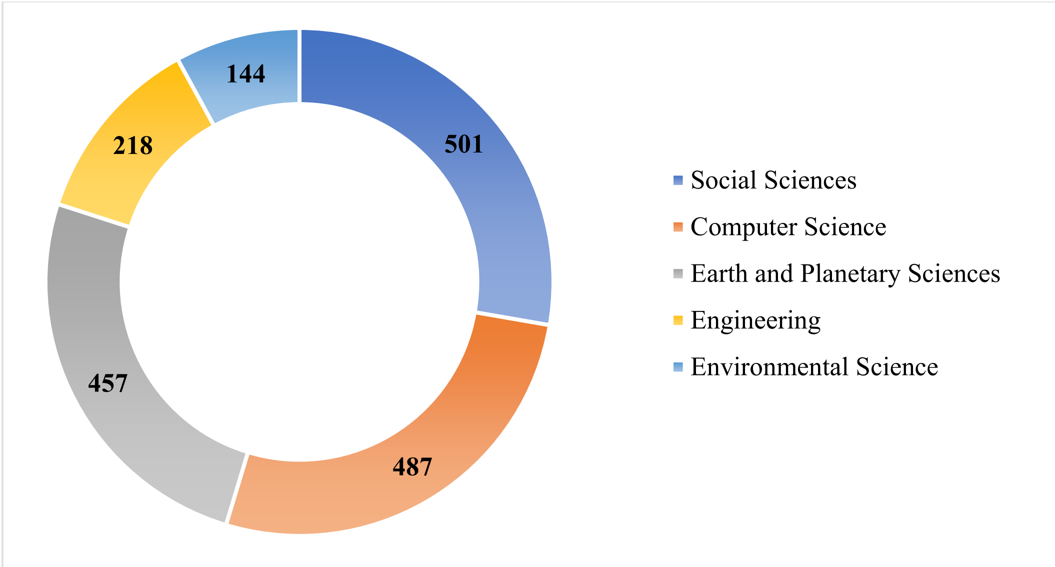


Figure 2.4. Top 5 VGI Research Domains Between 2007-2020. Source: (Scopus 2019).

VGI and Public Participation GIS (PPGIS)

Public Participation GIS (PPGIS) is another geographic information domain that is based on public voluntary processes. PPGIS refers to the use of GIS to support participation in planning management and decision-making, and it was initiated in the 1990s (Sieber 2006; Ganapati 2011). Verplanke et al. (2016) defined PPGIS as a process that "aims to represent local people's spatial knowledge by geographical information products most commonly, maps – that can facilitate informed and inclusive, participatory decision-making processes and support communication and community advocacy." Both VGI and PPGIS involve obtaining spatial information from non-experts (Brown and Kyttä 2014). According to Brown and Kyttä (2014), PPGIS often relies on active public involvement (i.e., direct data generation) in public processes like land use planning or community development; whereas VGI relies more on passive collection of spatial information through citizens who act as sensors. Also, citizens are more likely to use public datasets when participating in decision-making processes through PPGIS. In a

VGI context, citizens create, rather than necessarily use, their own data (Lin 2013). Still, the distinctions between PPGIS and VGI are not absolute, or absolutely clear, as some volunteers who are involved in VGI may have a propensity to participate in the process of decision-making when creating spatial information (Tulloch 2008).

In general, PPGIS is concerned more with processes, outcomes, and decision support participation (Verplanke et al. 2016), while VGI is focused on applications, and "large" spatial data collection (Elwood 2008; Engler, Scassa, and Taylor 2014). Furthermore, VGI is more focused on the dispersal and does not focus on the convergence of the activities (McCall 2003; McCall and Dunn 2012).

VGI Typology, Benefits, and Disadvantages.

Based on Craglia, Ostermann, and Spinsanti (2012), the typology of VGI includes two dimensions: (1) the way the information was made available, or "purpose"; and (2) the way geographic information forms part of it. Both dimensions can be either "explicit" or "implicit." Explicit refers to the information that represents a primary concern to the piece of the VGI in the dimension, while implicit represents a piece of information that was not originally an integral part in the dimension (or secondary). As an example, if part of the information includes a characteristic of a place, then that characteristic is considered explicit. On the other hand, if part of the information is not about a specific location but there is a possibility to geo-code it, it is considered geographically implicit. Similarly, information is explicit if it was made public by the author and contributed with a specific purpose. Conversely, if the information was made public, but the intention was not specific, the information is implicit. Table 2.3 illustrates the general typology of VGI.

Table 2.3. VGI Typology. Source: (Craglia, Ostermann, and Spinsanti 2012).

Volunteered Purpose Dimension	**Geographic Dimension**	
	Explicit	**Implicit**
Explicit	This is 'True' VGI in the strictest sense. Examples include Open Street Map.	Volunteered (geo)spatial information (VSI). Examples would include Wikipedia articles about non-geographic topics, which contain place names
Implicit	Citizen-generated geographic content (CGGC). Examples would include any public Tweet referring to the properties of an identifiable place.	Citizen-generated (geo)spatial content (CGSC) such as a Tweet simply mentioning a place in the context of another (non-geographic) topic.

Since VGI is mostly contributed and shared by individuals who lack formal training in geographic or cartographic theory or practice (also known as "neogeographers"), there is ongoing debate about the benefits and disadvantages of VGI (Elwood 2008; Engler, Scassa, and Taylor 2014). Several of these benefits and disadvantages are summarized in Table 2.4 as they relate to data, logistics, and social impacts.

Table 2.4. Benefits and disadvantages of VGI. Source: (Gouveia and Fonseca 2008; Engler, Scassa, and Taylor 2014).

Type	Benefits	Disadvantages
Data	• Support the development of early warning systems • Data collection for areas where no commercial or governmental interest exists • Big data – heterogeneous and multiple data sources for features • Rapid update of contextual information in times of change – i.e. construction, infrastructure, political upheaval	• Data credibility may be low • Metadata are scarce • Due to the volunteers' lack of specific knowledge and training • VGI is not always comparable to data collected by others • Unpredictable level of volunteer commitment
Logistics	• The participation of volunteers can be a cost-effective method to maintain data collection activities • Augment the geographic area and the time period being monitored	• Public participation may require training or close supervision of volunteer work • Requires the organization of training materials
Social Impacts	• More informed and educated public concerning environmental problems and scientific methods • Volunteer monitoring promotes cooperation instead of the traditional 'us versus them' approach	• The Not in my Backyard (NIMBY) principle, may affect citizen participation, distorting in some cases the goals of the volunteer initiative • Vandalism

VGI for Governments

The development of geospatial Web 2.0 (or Geoweb) is expanding the ways in which governments can interact with VGI to improve their processes, services, and service delivery methods. Geoweb is a set of online tools and data with geospatial capabilities to support citizen contribution in decision-making (Rouse, Bergeron, and Harris 2007; Ganapati 2010). By connecting citizens with government through internet-based communications, the transparency, efficiency, and effectiveness of public services can be improved (Brewer, Neubauer, and Geiselhart 2006; Dovey and Eggers 2008; Sæbø, Rose, and Skiftenes Flak 2008). There are two main reasons for governments to use VGI: (1) Citizens are regularly acting as additional sources or sensors for collecting data and information (Goodchild 2007) and, (2) VGI constitutes a type of citizen participation that governments value. However, Johnson and Sieber (2013) identified at least three reasons that governments might avoid using VGI: (1) cost, (2) data accuracy and reliability concerns, and (3) boundary issues.

Concerning the former, VGI can have financial (software and services) and human resources costs (e.g., training for VGI collection and processing). Second, VGI is contributed by a variety of individuals with, according to Goodchild (2007), no formal qualifications in the domain (contrast this scenario with the case in which GIS data are collected by credentialed experts). Since VGI contributors are heterogenous, VGI is characterized by informal, casual, and unstructured contexts (Flanagin and Metzger 2008; Elwood 2009). Third, VGI data occur across spatial scales (local to global) and, thus, they can create a jumping scale phenomenon (Smith 2012; Cox 2017). Jumping scale refers to a situation when individuals operating at a fine resolution (e.g., community) circumvent an intermediary scale of decision-making (e.g., municipal scale) to bring an issue at a higher scale (e.g., federal scale) (Swyngedouw 2004; Cox 2017). This cross-scale nature of VGI is an obstacle and may not fit with preferred local government decision-making structures. To overcome these challenges, Johnson and Sieber (2013) recommend increasing the formalization of VGI collection, encouraging collaboration across governments, and investigating the participation potential of VGI.

VGI and Social Media (SM)

One main characteristic of VGI is the collaborative process of data production through different platforms. One of these platforms is Social Media (SM). SM is defined as a group of technologies where individuals participate in creating, organizing, editing, combining, sharing, commenting, and rating web content as well as forming a social network through interacting and linking with each other (Chun et al. 2010). From a governmental perspective, SM can be defined as a group of technologies that allow public agencies to foster engagement with citizens and other organizations using the philosophy of Web 2.0 (Criado, Sandoval-Almazan, and Gil-Garcia 2013). The interactivity and voluntary characteristics of SM overlap with the notion of co-production and open up new promises for it (Linders 2012). During the past few years, SM has gained significant popularity and growing adoption among governments (Lovejoy and Saxton 2012; Nah and Saxton 2013). Some SM platforms, such as Twitter, are known as location-based platforms through which the user can share content attached to a geographic location. By using the geographic content from SM, researchers have leveraged SM data in studies of such phenomena as disasters and emergencies (Aula 2010; Guan and Chen 2014; Kryvasheyeu et al. 2016), urban structure (Huang and Wong 2016), and citizen-government interactions (Eshleman and Yang 2014; Gao 2018).

The number of internet and SM users is increasing, creating limitless potential for VGI. In 2019, according to Dave Chaffey (2019), there were approximately 4.4 billion internet users (about 9% increase in a year) and about 3.5 billion active SM users. At the global scale, Facebook had the biggest portion of active users among SM platforms, with more than 2.2 billion active users. The top 20 SM platforms, in terms of active users in 2018, are presented in Figure 2.5. The majority of these active users (in the case of Facebook, Instagram, and Twitter) are daily users, as summarized in Figure 2.6. Building on these facts, considering SM as a significant source of enhancing urban commons should not be regarded as trivial by local governments, especially with the location-based nature of SM data.

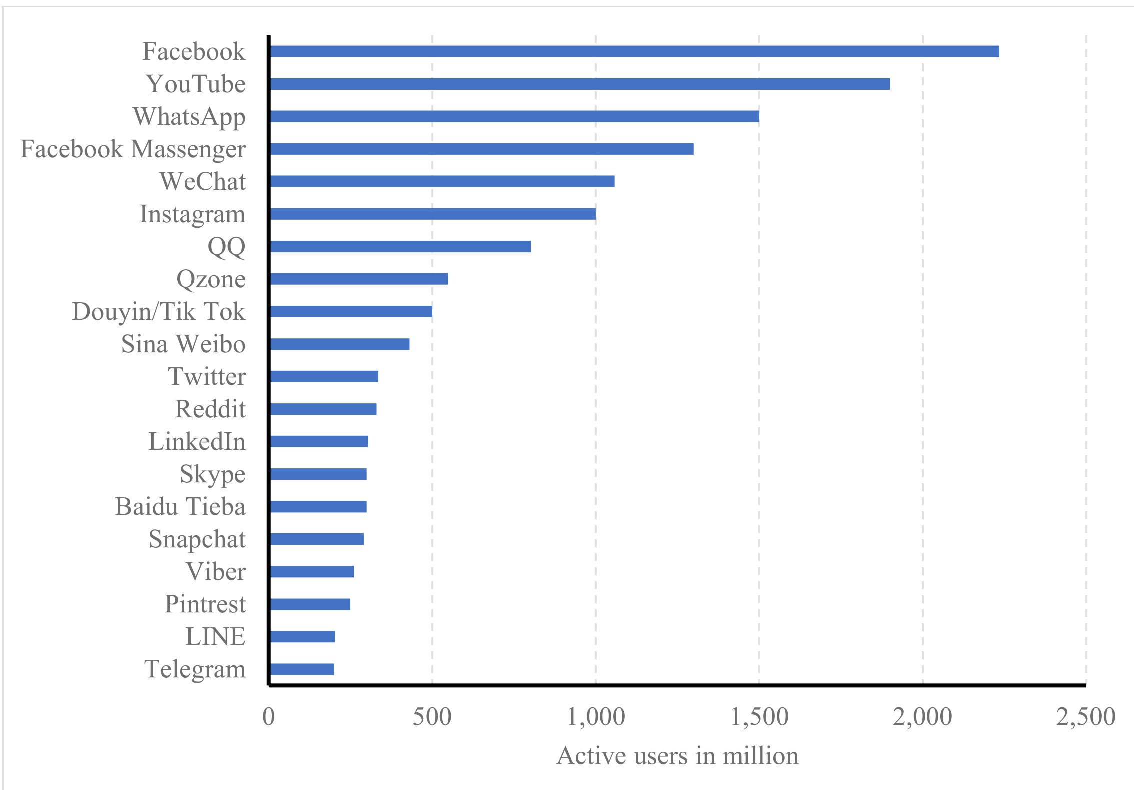


Figure 2.5. Most Popular Social Networks Worldwide in 2018. Source: (Dave Chaffey 2019).

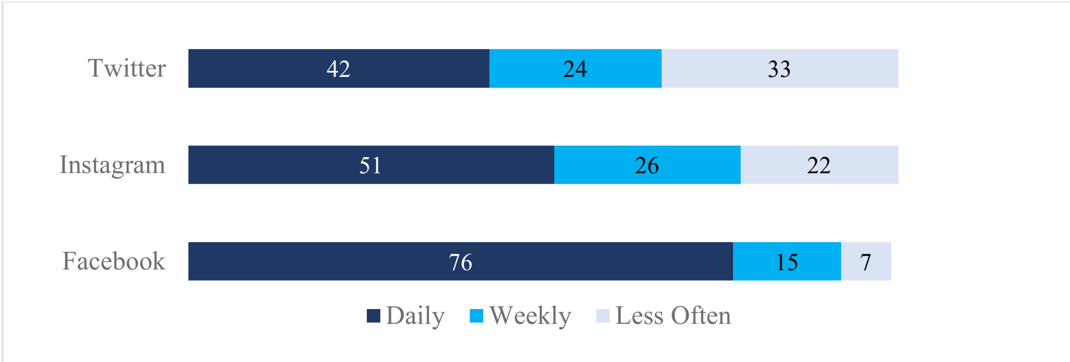


Figure 2.6. Temporal usage by Active Users of Facebook, Instagram, and Twitter in 2016 in Percent. Source: (Dave Chaffey 2019).

VGI and Geographic Research with 311 Data

Volunteered Geographic Information (VGI) and other data from 311 systems have been used on several occasions in studies on citizen-government interactions and to evaluate spatial patterns of public services. These patterns are often found to vary systematically with local socioeconomic characteristics. Specifically, socioeconomic characteristics have been used to classify neighborhoods (Wang et al. 2017), explain the spatial distribution of 311 volumes across different neighborhoods (Minkoff 2016), identify preferred 311 communication channels (Lu and Johnson 2016), investigate the extent to which territoriality and connected motivations explain certain types of 311 issues (O'Brien 2016b), quantify request frequencies (Cavallo, Lynch, and Scull 2014), and analyze residents' propensity to use 311 systems (Kontokosta, Hong, and Korsberg 2017). Common practices in these studies, which are habitually based in the U.S., include adopting the census tract level as the geographic resolution of analysis (Cavallo, Lynch, and Scull 2014; Minkoff 2016; Wang et al. 2017), applying machine learning techniques (Eshleman and Yang 2014; Wang et al. 2017), and using 311 data from large cities such as New York City (Cavallo, Lynch, and Scull 2014; Eshleman and Yang 2014; Minkoff 2016; Kontokosta, Hong, and Korsberg 2017).

In their efforts to use 311 service requests to improve neighborhoods classification, Wang et al. (2017) developed a method to explore the potential for using 311 data as proxies for socioeconomic characteristics. Their approach used machine learning at the census tract level. They collected 311 data across more than 30 cities in the U.S., including NYC, Boston, and Chicago. Socioeconomic and demographic data were collected from the U.S. Census Bureau and were used to ground truth results from the model. The hypotheses of the study were that the spatiotemporal patterns of 311 requests should be similar across a city or cities, and that similarities in complaint patterns should mirror similarities in socioeconomic characteristics across the study areas. They applied k-means clustering to classify request patterns in the studied cities. In NYC, for example, they identified four clusters based on volume and type. The most common complaints by cluster were: noise concerns in cluster 1; residential heating in cluster two; blocked driveways in cluster 3; and street conditions in cluster 4. Each cluster took on a distinctive socioeconomic and demographic profile. Residents in cluster 1 had relatively high education and income, which was the opposite of cluster 3. Clusters 1 and 2 contained a higher concentration of Non-Hispanic White residents, whereas cluster 4 contained more residents of Asian origin and cluster 3 contained more African American residents. The same approach was applied for Chicago and Boston, and similarities to NYC in the relationships between complaint type and resident composition were observed.

Similarly, Minkoff (2016) used socioeconomic attributes to explain partial variation in the spatial distribution of 311 requests in NYC at the census tract level. He examined both place-based complaints regarding the quality of government goods (e.g. waste collection and streets), and human-based complaints related to negative externalities or incivilities (e.g. noise). His analysis used an Ordinary Least Squares (OLS) regression model to examine the associations between complaints and a variety of control variables. The study found that higher complaint levels are associated with older housing, vehicle traffic, and high population growth. Complaints about place-based issues were higher in areas of the city with more homeowners. Oppositely, complaints about negative externalities from human actions (human-based complaints) occurred more frequently in areas with fewer owner occupants.

Another analysis of 311 data was the analysis of preferred communication channels and their associated sociodemographic variables in the city of Edmonton, Alberta, Canada (Lu and Johnson 2016). 311 and sociodemographic data for the city of Edmonton were collected between 2013 and 2015. The analysis of the data included a comparison of relative request share for each channel, geographic hot spot analysis, and regression. Their study found that there was a shift in 311 channels from traditional voice-based to internet-based channels over time—consistent with the notion that creating technology-based platforms results in greater uptake of such systems, suggesting that governments should seek to provide a diverse menu of reporting options for citizens. In addition, the study found spatial differences between reports generated through specific channels. One of the findings was that internet-based channels showed more significant hotspots at a broader geographic range compared with traditional channels.

This finding suggests that internet-based channels are more mobile, which reflects the speed of reporting or responsiveness of individuals. In terms of sociodemographic characteristics and 311 channels, the study found that older people tend to use the telephone while younger people make more internet-based requests.

In another study, O'Brien (2016b) explored whether territoriality motivations can act as a proxy for 311 calls relating to incivilities or negative externalities from human activities in Boston, Massachusetts. The study consisted of two main components. First, it identified whether individuals (311 users) have tendency to report a certain type of request. Second, it examined whether particular territorial motivations influence individuals to use 311 as a means to exert social control over shared spaces. The study used 311 data from 2010 and 2014. In addition, a survey was conducted to collect behavioral and socioeconomic data from a targeted group of 311 users who provided data used to operationalize two dimensions of territoriality (benefitting the local community and enforcing norms). The survey also asked respondents to optionally provide socioeconomic information (e.g. sex, age, income, and education). The data were analyzed through multiple methods including descriptive statistics, correlation, clustering (for geographic patterns), and a general linear model. The study found that individuals tended to specialize in reporting either natural deterioration of place-based features (e.g. reporting potholes) or human-based negative externalities/incivilities (e.g. graffiti), but not both. In other words, reporters had different behavioral patterns. According to the geographic distribution analysis, reports of incivility tended to be near individuals' homes. The desire to enforce social norms was higher in individuals who reported incivilities, whereas the desire to create community benefits was more closely associated with place-based complaints.

Another study that bridged SM and 311 data (perhaps the first such study to do so) sought to investigate the spatiotemporal relationships between the sentiment aspects of tweets and 311 civil complaints (Eshleman and Yang 2014). The study collected three datasets; (1) GlobalTweets collected from five cities (San Francisco, NYC, Los Angeles, London, and Sydney), (2) SFTweets (originating from San Francisco), and (3) 311 data from the City of San Francisco. The sentiment analysis was carried out using machine learning algorithms and a "Happiness Index" (ranging between -1 and 1, where 1 is the highest possible happiness sentiment) to explore sentiment variations. The study found a positive relationship between local sentiment and government responsiveness.

Furthermore, Cavallo, Lynch, and Scull (2014) explored the relationship between sociodemographic characteristics and 311 request frequency in three U.S. cities (NYC, San Francisco, and Washington DC) using GIS (for quantitative and thematic visualization) and regression analysis. The data for the three cities were collected from Open311 (an open-source data platform). For standardization purposes, the analysis was limited to requests in 2011. The sociodemographic data were collected from the US Census Bureau and the American Community Survey. The data included gender, race, ethnicity, age, income, citizenship status, housing tenure, and parental status. 311 data were aggregated to the census tract level for count and summary analysis. To model how demographic characteristics vary with service requests, an OLS model regressed count of requests on several independent variables. The study found that areas with higher percentages of lower-income households, older citizens, women, African Americans, Latinos, and households with children submitted fewer service requests, indicating that these demographic groups are underrepresented in 311 systems. Similarly, Kontokosta, Hong, and Korsberg (2017) aimed to analyze the variance in the propensity to use the 311 system and to understand the relationship between socioeconomic, demographic, and cultural factors and complaint behavior in NYC in 2016 at the census block level. They developed a two-step methodology to (1) predict the likelihood of heating and hot water violations for a given building and (2) compare the actual complaint volume for buildings with predicted violations to quantify discrepancies across the city. The dataset included complaints from 311 service requests (with a focus on heat and hot water complaints), the physical condition of buildings integrated with heat and hot water-related violations, and demographic and socioeconomic data from the U.S. Census Bureau. The study found that neighborhoods that tended to under-report to 311 had higher proportions of male residents, unmarried residents, and persons of color; a higher unemployment rate; and more limited English speakers. These less advantaged population subgroups were underrepresented in the 311 system, even though many likely experience heat and hot water problems in their building. Neighborhoods that tended to over-report issues were those with higher rents, higher household incomes, and a higher proportion of female, elderly, and non-Hispanic White and Asian residents, with higher educational attainment. In summary, socioeconomic status, household characteristics, and language proficiency have a significant effect on the propensity to use 311 in New York City.

Despite the rapidly increasing use of 311 systems and the growing body of academic research on these systems, there are several important areas of research that remain under-explored. Several aspects of socioeconomic and demographic characteristics were used to identify how local communities may have disparities in 311 request volume due to the impact of the *Digital Divide* (e.g., Cavallo, Lynch, and Scull 2014; Lu and Johnson 2016; Minkoff 2016). However, the integration of technology usage statistics was overlooked. Technology statistics, including computer and internet usage, could sharpen the model results in previous studies. In this dissertation, the community's technological skills statistics in Kuwait were included for the models in Chapter 5, which will be explained in greater detail.

In addition to the latter point, the opportunities for additional research, which are enumerated in the following section, are the main gaps in the literature to which this dissertation is directed.

Gaps in the Literature

As discussed above, numerous scholars have demonstrated how 311 requests can be combined with socioeconomic and spatial data to reveal how the channels of communication may vary among users, how differences in socioeconomic status may result in under or over-reporting behavior, and how certain people may prefer to submit certain types of requests. Moreover, the literature has established the ways in which VGI, and more specifically SM, contribute to citizen-government interaction as a new and increasingly convenient channel of communication for citizens.

However, there are several gaps in the literature that remain under-investigated. These gaps, in general, deal with the lack of spatiotemporal pattern analysis at both global (point pattern) and local (high/low) level of complaints in overall and at the detailed complaint type. Furthermore, there was limited research that examined the factors that may contribute to more and/or faster responsiveness from local government to complaints. Additionally, there are few if any studies that use geovisualization methods to examine citizen-government interaction indicators and agency interconnectivity. Finally, exploring complaints produced, disseminated, and organized by informal, non-authoritative, voluntary activity – as opposed to forma, government-sponsored 311 systems – represents a unique contribution of this research. Doing so in the non-U.S. context of Kuwait makes the research even more unique and timely; and the results have important policy implications for the potential success of (and demand for) implementing a centralized public service system in Kuwait.

3. STUDY AREA, DATA COLLECTION, PRE-PROCESSING, AND RELATIONAL DATABASE DESIGN

As discussed in Chapter 1, citizen complaints about governmental services (or goods) can be shared through various sources, including phone calls, face-to-face locations, mobile applications, and social media (SM). The latter represents a unique research opportunity, especially in Kuwait, where a group of volunteers recently established a principal contact point for receiving citizen-generated complaints about governmental goods and services. These complaints are submitted by citizens and received by the voluntary group. Complaints are then broadcast to the responsible governmental agency. Thus, the SM account is mid-point of communication between citizens and government (Figure 3.1).

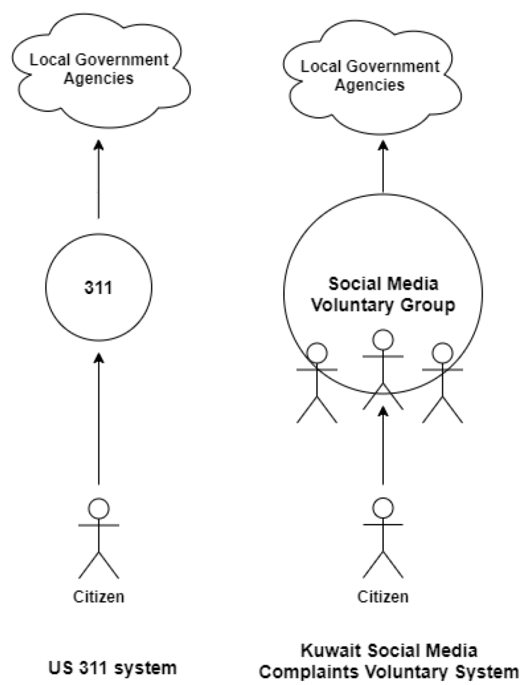


Figure 3.1. A general comparison in the citizen complaint process between the US 311 system (on the left) and voluntary citizen social media approach in Kuwait (on the right).

This chapter provides background information on the study area, the State of Kuwait, and describes the data, data collection, pre-processing steps, and relational database design used in the subsequent chapters. The chapter concludes by summarizing the data, uncertainty in the data, and key limitations.

Study area background

After the export of the first oil barrels in the mid-1940s, Kuwait, a small town depending on the sea as a primary resource of food and trading, adjacent to desert, entered a new era of massive state-building and centralization (Al-Nakib 2016). With the new source of wealth, the city entered a phase of rapid growth through urban planning strategies developed in collaboration with British planners (Minoprio, Spencely, and MacFarlane 1953). The new plans to develop the country provided new job opportunities and better income sources for local and international workers. These opportunities led to massive immigration and movement from neighboring countries, or from the local desert, to take advantage of new jobs in the oil, construction, and service sectors (Lienhardt 1993).

Job related in-migration rapidly increased Kuwait's population and influenced the demographic makeup of the country. At the time of the country's first census in 1957, non-Kuwaiti citizens accounted for 45% of the total population (92,851). The Kuwaitis population at that time was 113,662 residents (Central Statistical Bureau 2020c). Since 1957, Kuwait's population has undergone almost constant growth, with the exception of in the early 1990s due to the Iraqi invasion. The population reached ~4.8 million by 2019 (Public Authority for Civil Information 2019). This large-scale urban growth means that the Kuwaiti government is responsible for providing essential sustainable development plans to meet the population demands for public services, including health care, residential services, power supply, transportation systems, and other services

Geography of Kuwait

Kuwait is located between latitudes 28°30´, 30°05´ North and longitudes 46°33´, 48°30´ East on the north-eastern part of the Arabian Peninsula, sharing borders with the Kingdom of Saudi Arabia and the Republic of Iraq with a total area of ~18,000 km^2 (Figure 3.2).

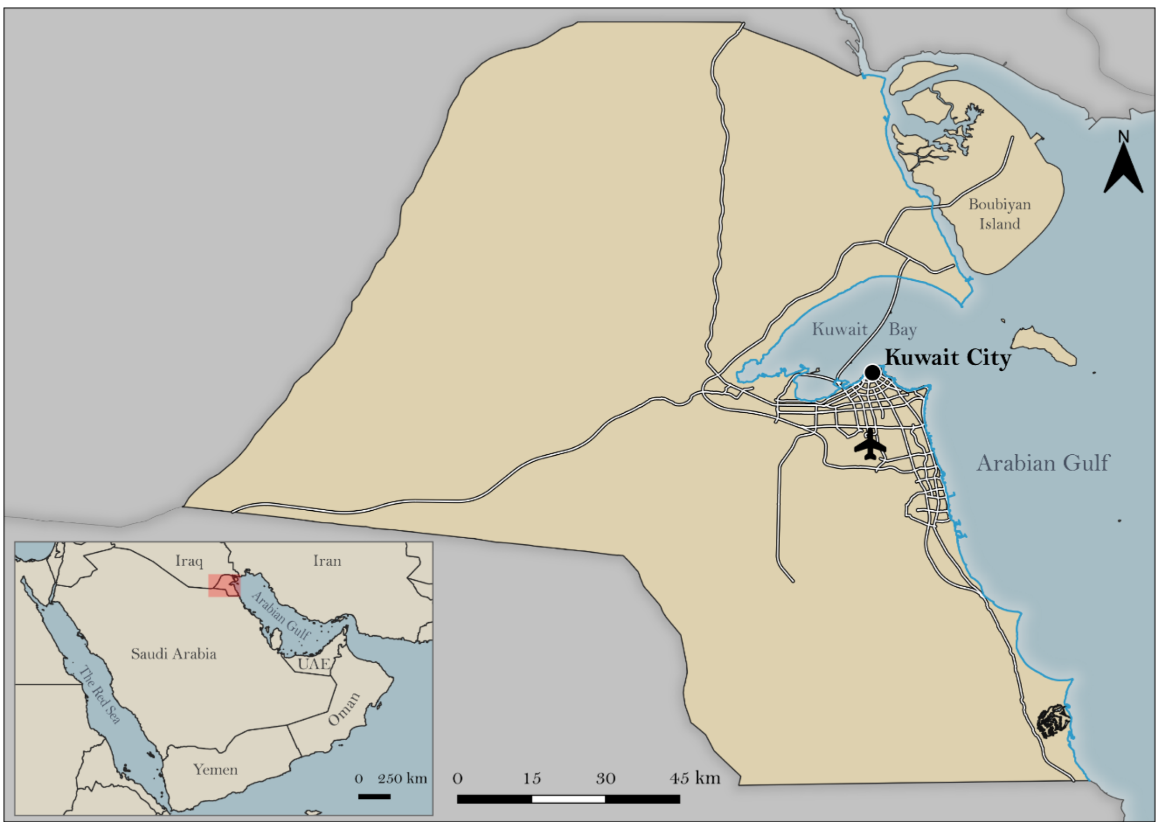


Figure 3.2. **Study area.**

Kuwait's climate is a hyper-arid (hot and dry) desert region climate with an average yearly rainfall of approximately 116 mm. The average temperature in July is

~50°C and in January is ~13°C (Al-Yamani et al. 2004). A smooth surface characterizes Kuwait's topography with elevation increasing from the coastlines in the east towards the west of the country, and the maximum elevation is about 300 m above mean sea level.

Kuwait's urban area is approximately 878 km^2, and about 97% of Kuwait's population lives in urban areas (Alsahli and Al-Harbi 2018). With the increase of population growth and demands, expanding the current urban area and developing economic and recreational projects became essential to sustain local quality of life. Therefore, both the government of Kuwait and the private sector have planned for and accomplished multiple projects in recent years, with several projects currently under construction (Figure 3.3).

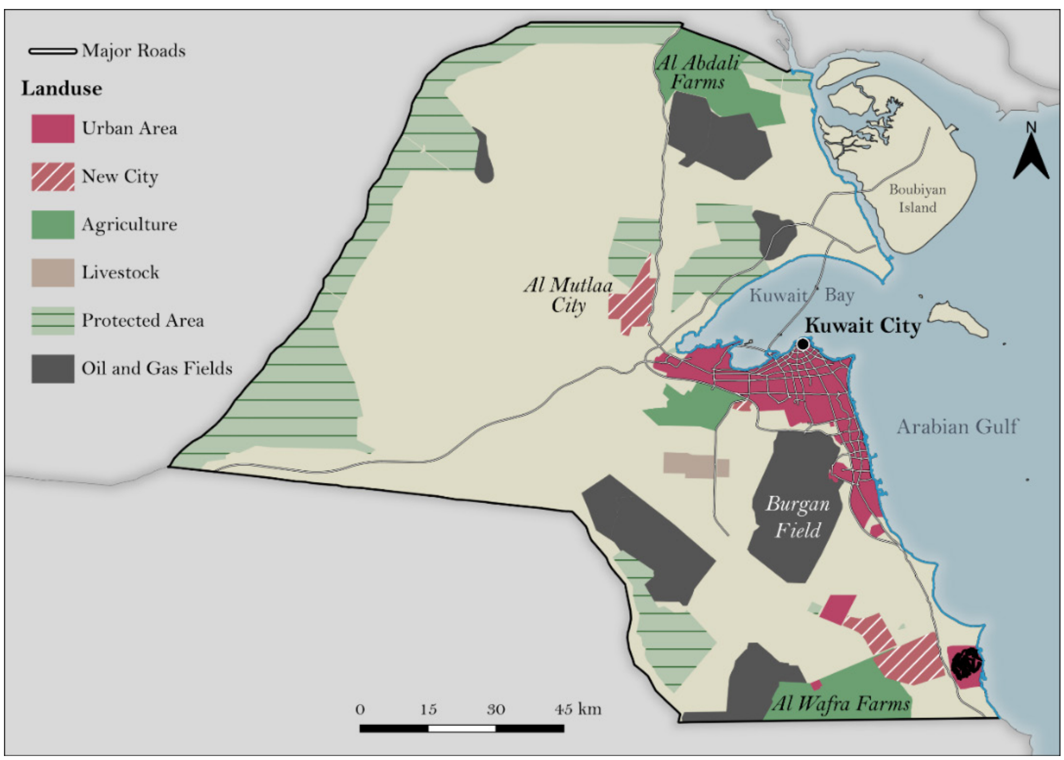


Figure 3.3. Current and future land development in Kuwait. Generalized data were re-created after Kuwait Municipality (Kuwait Municipality 2013) and the Environmental Public Authority of Kuwait (Environmental Public Authority (EPA) 2020).

Consequently, rising demand for urban public goods will continue to present a challenge. The population in Kuwait has seen continued growth since the Iraqi invasion in 1990. Change in total population since 1990 is depicted in Figure 3.4. During 1990, the total population was 2.15 million. Population dropped to 1.65 million (23.5%) after the invasion in 1993. However, by 2019, the total population reached 4.78 million (Public Authority for Civil Information 2019). Corresponding with population growth, in 2015, roughly 1.9 million vehicles were active on Kuwait's road systems – a number that count rose to approximately 2.1 million in 2017 (Central Statistical Bureau 2020b).

Alongside permanent population growth, migration and temporary residence in Kuwait is also trending up. In 2016, the number of residency requests was about 2.6 million, and grew to 3 million in 2019 (Central Statistical Bureau 2020d). Once again, available indicators suggest that demand for urban public goods, and frequency of non-emergency requests, should be expected to grow across Kuwait.

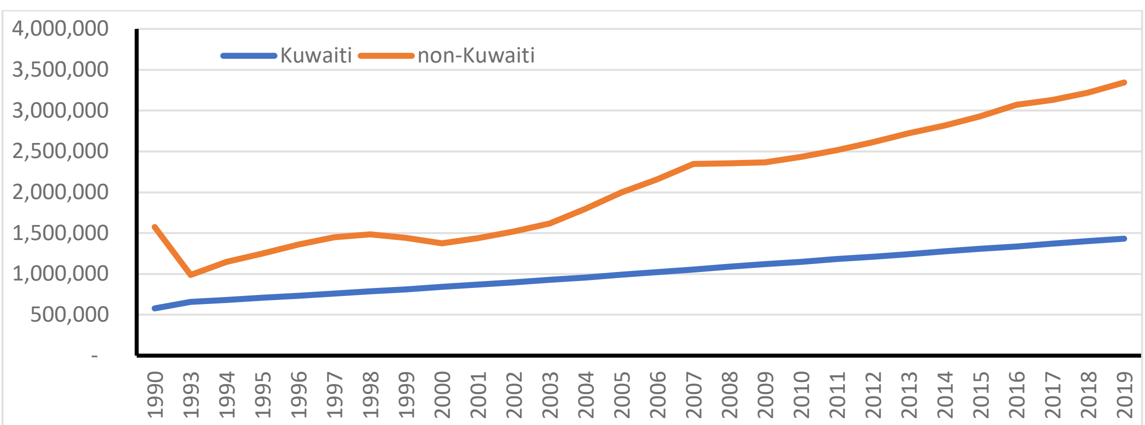


Figure 3.4. **Kuwaiti and non-Kuwaiti population**. Source: (Public Authority for Civil Information 2019).

Kuwait is organized into three geographic administrative levels. The highest level, with the largest spatial extent, is the governorate level; the second is the neighborhood level; and the third, finest resolution level is the block. The administrative levels in Kuwait are shown in Figure 3.5. Understanding the nature of land boundaries in Kuwait is essential for performing geographic analysis on social phenomena like citizen complaints. Details regarding the selected administrative level for analyses are provided later in this chapter.

Figure 3.5. Administrative levels in Kuwait.

Data collection and pre-processing

Data collected for this research included:

- Citizen complaints from SM.
- Census data
- Real estate prices

The following sections provide details on each of these three data categories.

Social media complaints

Kuwait had an estimated 3.9 million SM users in 2019, 79.5% (3.1 million) of which were mobile SM users (Simon Kemp 2019). Up to December 2019, there were 1.9 million Instagram users in Kuwait. Males accounted for 61.5% of all users, and users between 18 and 44 years old made up 89% of all users (NapoleonCat 2020). One of Kuwait's nearly 2 million Instagram accounts was created by a group of Kuwaiti volunteers to receive and share complaints from citizens and communicate with the government regarding these complaints (*Q8needsyou*[2]).

In the Q8needsyou account, posts are shared with detailed information, including the complaints address (location), time, type of complaint, responsible agency, the gender of the reporter, if the complaint was resolved, post engagement (count of likes), and the complaint's nature (natural deterioration or incivilities). Such information was extracted using both manual and automated processes since Instagram posts are not well structured. After extracting the required information, a relational database was designed and created to store the collected data. An example of a post with some of the included information is provided in Figure 3.6. For seasonal analysis purposes, all posts shared during 2019 were collected.

[2] https://www.instagram.com/q8needsyou/?hl=en

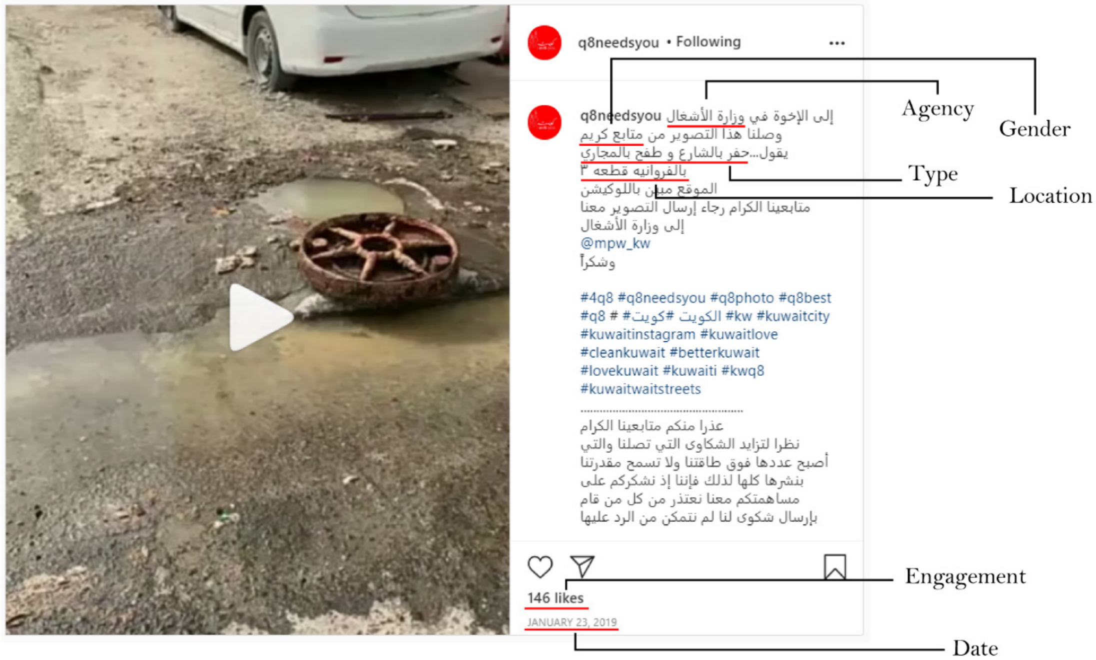


Figure 3.6. An example of an Instagram post with information about the complaint.

Post-level data collection from the Instagram account was done through *web scraping*. The library used for this purpose was *Selenium* in the Python programming language. Selenium provides several functions to select and fetch required information from the post (e.g., date or likes) and store it in a Python list. The collected data included the complaint date, text, likes, and the URL of the post. The process of collecting the information from every Q8needsyou post is outlined in the diagram in Figure 3.7. First, Selenium opens the required webpage through a web driver (e.g., Chrome). Then, a *for loop* was used to get the necessary information from the post. The number of loops was set to 10,000 since the number of required posts was unknown, and it was assumed that 10,000 loops would capture all of the 2019 posts. Once all the data were collected from a post, a *click* function was used to navigate to the next post. During each iteration, the data collected were stored in lists. Finally, all lists were saved in a final table.

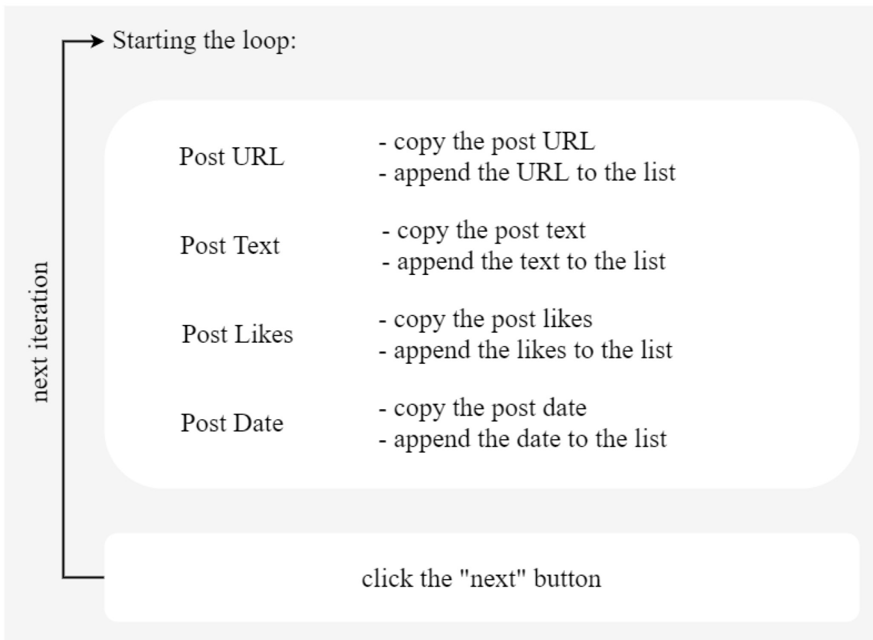
Instagram post scraping process

1- open web driver

2- go to webpage (https://www.instagram.com/q8needsyou/?hl=en)

3- click on the first post (the element id of the first post was obtained manually)

4- looping through each post



5- saving the collected data to a table

A	B	C	D	E
id	link	text	likes	time
4	https://www.instagram.com/p/BsELmxoFLw3/	q8needsyouكل عام وانتم بخير54w	130 likes	1/1/2019 2:35:58
6	https://www.instagram.com/p/BsHzPImlpfl/	q8needsyouم إلى الإخوة في وزارة الأشغال	152 likes	1/2/2019 12:19:59
7	https://www.instagram.com/p/BsHzv3FFDjv/	q8needsyouشكل غير معقول يا أشغال ؟	144 likes	1/2/2019 12:24:27
12	https://www.instagram.com/p/BsH7pielbZy/	q8needsyouم اخوي إلى الإخوة في البلدية	127 likes	1/2/2019 13:33:30
15	https://www.instagram.com/p/BsH8Tf5lr6T/	q8needsyouبالشوارع وفوق الأرصفه ؟	182 likes	1/2/2019 13:39:13
16	https://www.instagram.com/p/BsH_M7wlf7v/	q8needsyouالأشغال في صيانة الشوارع	121 likes	1/2/2019 14:04:32
17	https://www.instagram.com/p/BsH_WAulBLP/	q8needsyouبهذا تصرف يا إدارة المرور ؟	133 likes	1/2/2019 14:05:47
20	https://www.instagram.com/p/BsIKcawlWPX/	q8needsyouن رقابة وحزم إدارة المرور ؟	182 likes	1/2/2019 15:42:46
22	https://www.instagram.com/p/BsIK3R4F4xK/	q8needsyou.صيانة الشوارع يا أشغال ؟	141 likes	1/2/2019 15:46:26
26	https://www.instagram.com/p/BsIe55ylZ7-/	q8needsyouخوة في إدارة حديقة الشهيد	135 likes	1/2/2019 18:41:34
28	https://www.instagram.com/p/BsI8DRqFb8X/	q8needsyouالفين عند مجمع الأفنيوز ؟	143 likes	1/2/2019 22:56:15

Figure 3.7. **Instagram post web scraping workflow**. The workflow was done through the Python programming language using the *Selenium* library.

Based on the post text description, further information was extracted. Starting with location, each post was geocoded manually. Address included in posts were not structured in a way to enable geocoding automation. The geocoding was done by creating a GIS point layer and adding a point at the described address location. Each point was assigned the same complaint-level id to be joined later in the relational database. Locational information was not consistent in spatial resolution and varied according to the precision of citizen descriptions and the local knowledge of the reporter. Some posts included an address up to the house level; others were reported at the neighborhood level. Such notes were also collected to classify the posts based on their spatial scale for spatial analysis.

Next, complaints were classified based on their type. No consolidated list of types exists, either in the Instagram account or in any U.S. 311 system (each 311 adopter defines its own custom list of complaint types based on local context). As an example, NYC311 includes 182 complaint types, while Chicago has only 12 types (Wang et al. 2017). Therefore, this research developed a hybrid complaint type that overlaps with the common types in major systems such as NYC. The developed list of types in this research with examples is included in Table 3.1. Based on the description of each post, a complaint type id was assigned. The extraction of the type was done manually, based on the content of the complaint.

After being assigned a type, extracting the nature of each complaint was the next step. Based on the description provided, a complaint was classified into natural-based (natural deterioration), human-based (incivilities), or mixed (both). Natural-based complaints are caused by natural factors such as street potholing or streetlight damage. In contrast, human-based complaints are negative externalities caused by human activities, such as speeding or illegal dumping of waste. Complaint classes were assigned manually for each post.

Table 3.1. **Complaint types in Kuwait.**

Type id	Type	Example
1	Traffic	Speeding vehicles
2	Municipal	Municipal waste
3	Infrastructure	Street pothole
4	Utilities	Streetlight outage or water leakage
5	Landscape	Overgrown trees in front of houses
6	Environment	Dumping waste to the sea
7	Social	A child selling items on the street
8	Administrative	Absent employees in governmental service facilities
9	Mixed	Multiple types in one complaint

Next, the name of the agency tagged in each post was collected through an automated process. Each complaint included at least one agency name. Using a developed list of agency names collected from the posts (Table 3.2), and through a script written in a *Structured Query Language* (SQL), a condition was made to assign an agency id for a post if it included a specific keyword. For instance, if a post had the word "mun," it was designated the Municipality's id from Table 3.2. In some cases, a complaint may include multiple agencies thus will have multiple IDs.

Finally, complaints that were resolved were also collected in a separate table. This process was done manually. First, all complaints mentioning words that indicated fixed complaints were identified. Such complaints featured words of appreciation, such as “we acknowledge the municipality's work and their response…” These resolved complaints were stored in a separate table with their id and time. Then, each resolved complaint was examined to identify the address and the type of complaint to search back in time for a complaint with the same description. If found, the id and the time of the original complaint were also captured. By the end, each row in the resolved complaints table consisted of the responded complaint id and time with the original complaint id and time. This table allows for approximate measures of government response time for each complaint. An example of a fixed/resolved and original complaint is provided in Figure 3.8.

Table 3.2. **Identified agencies mentioned in the complaints.**

Agency id	Agency abbreviation	Agency name
1	MUN	Municipality
2	MPW	Ministry of Public Works
3	MOI	Ministry of Interior
4	MEW	Ministry of Electricity and Water
5	MOH	Ministry of Health
6	APF	Awqaf Public Foundation
7	MSAL	Ministry of Social Affairs and Labour
8	PAAF	Public Authority for Agricultural Affairs and Fish Resources
9	NCCAL	National Council for Culture, Arts and Letters
10	PACI	Public Authority for Civil Information

Agency id	Agency abbreviation	Agency name
11	EPA	Environmental Public Authority
12	PAM	Public Authority for Manpower
13	PAS	Public Authority for Sport
14	PART	Public Authority for Roads and Transportation
15	PAHW	Public Authority for Housing Welfare
16	PAAET	Public Authority for Applied Education and Training
17	PAI	Public Authority for Industry
18	CITRA	Communication and Information Technology Regulatory Authority
19	TEC	Touristic Enterprises Company
20	DGCA	Directorate General of Civil Aviation
21	MOJ	Ministry of Justice
22	MOC	Ministry of Communications
23	KPA	Kuwait Ports Authority
24	KFD	Kuwait Fire Department
25	MOD	Ministry of Defense
26	KPTC	Kuwait Public Transportation Company
27	MOE	Ministry of Education
28	MOCI	Ministry of Commerce and Industry
29	GAC	General Administration of Customs
30	KU	Kuwait University
31	MI	Ministry of Information
32	KOC	Kuwait Oil Company

Like the agency extraction process, an SQL script was written to assign a gender id if a particular keyword was included in the post's text. All the required information from the

SM complaints was extracted and stored in relational database tables. Further details regarding the database are provided later in this chapter.

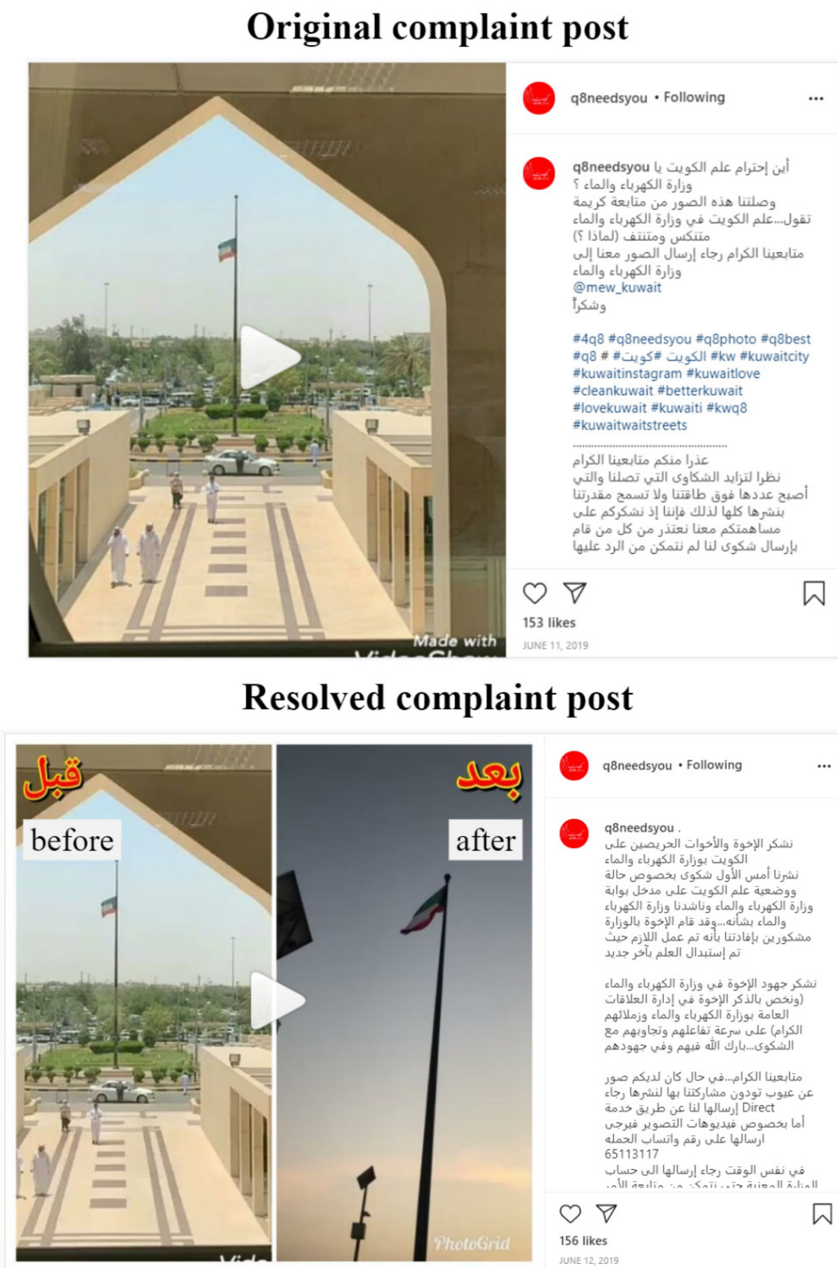


Figure 3.8. **An example of a responded and original complaint.**

Census data

Data on factors that may correlate with citizen complaints—namely, socioeconomic and demographic data—were collected from the Geoportal of the Central Statistical Bureau of Kuwait (Central Statistical Bureau 2011). The most recent full census data for Kuwait were collected in 2011. The data were available at all administrative levels and touch on four main census themes: (1) population, (2) household and housing conditions, (3) buildings, and (4) establishments. Each theme consisted of multiple measurements or variables. Specific variables from each theme were selected for the analyses in this dissertation in consultation with instructive literature (e.g., Minkoff 2016). These variables are listed in Chapter 5, where they are used as explanatory variables in regression analyses. The census data were available in absolute numbers and percentages. For normalization purposes, percentages were used in place of raw counts.

Real estate data

Unlike in the U.S., the census in Kuwait does not capture household or individual income data. As such, real estate prices were used as a proxy. Reports from Kuwait Finance House (KFH) (Kuwait Finance House 2020), a local bank, were collected to get the real estate prices per m^2 in Kuwaiti Dinar (KD). These reports were available quarterly through 2019. The prices were reported at the neighborhood level and categorized based on the land type. In general, there are four major land types: (1) private housing, (2) investment, (3) commercial, and (4) industrial. Business groups usually own the latter three land types. Thus, they do not reflect individual income. Therefore, neighborhoods with private housing prices were used in this research. A map with the real estate land categories is shown in Figure 3.9.

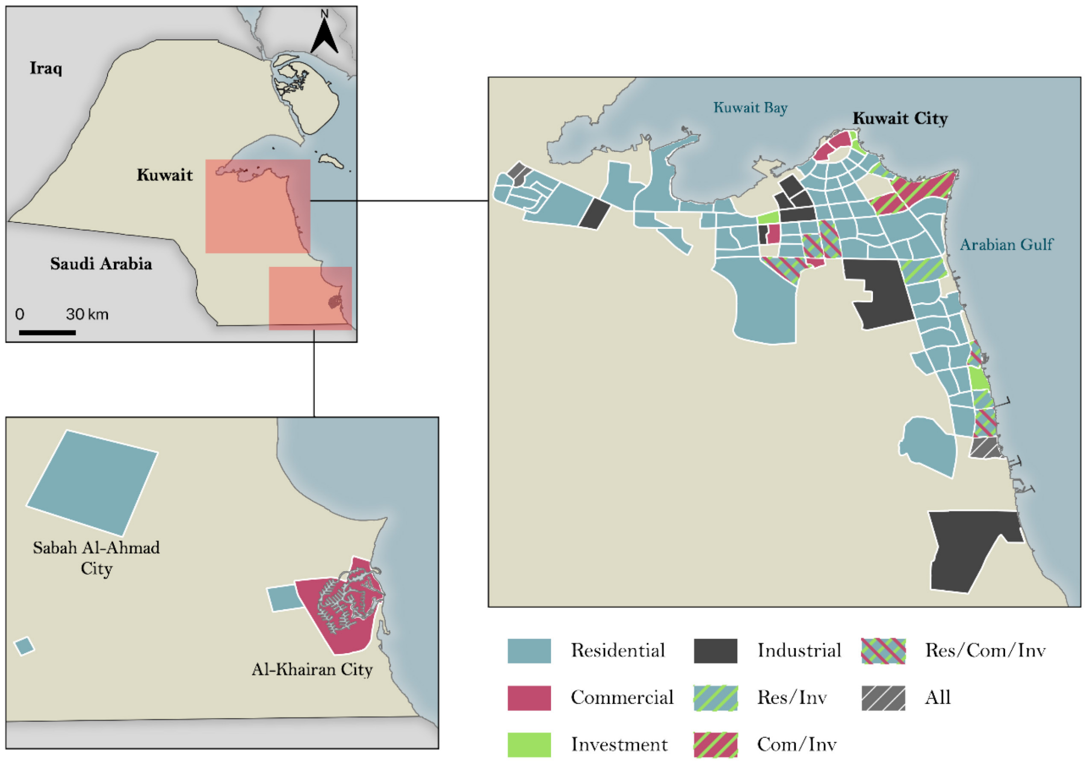


Figure 3.9. **Real estate land categories.** It was created after the real estate price reports from KFH (Kuwait Finance House 2020). Only areas with private housing prices were included for the spatial analysis. The land types on the map are based on the classification detailed in the reports.

Relational database design

After collecting the data described above, data were stored in a relational database to enable further data queries to serve each analytical chapter. The database design and *Entity Relationship Diagram* (ERD) of this dissertation are illustrated in Figure 3.10. There are seven tables that contain information regarding citizen complaints (highlighted in red bounding box). The main table, “complaints_t”, consists of several fields, including complaint id, time, text, link, and multiple complaint characteristics. The primary key (PK) “id” is the join field in the database. Another table, “response_t”, stores resolved complaints and the original cases, along with their timestamps, to investigate responsiveness in Chapter 5. The “agency_t” table contains the agencies involved for each complaint. Finally, four tables store complaint characteristics, such as the type or agency names.

In addition to complaints, the databased contains two tables with census data (highlighted in blue bounding box). Both tables feature data on the same themes and variables, but at two different administrative levels (neighborhoods and blocks). Also, a table with real estate prices contains the average residential price by geography for 2019 (in the blue area). Finally, multiple GIS layers (highlighted in green bounding box) were used for spatial analysis and to link both census and real estate data with citizen complaints at any given admin-level. The GIS layers were the boundaries of each admin-level in Kuwait and buffered primary roads within the metropolitan area. The metropolitan area will be discussed further in Chapter 4.

The main ERD in Figure 3.10 was used as the data repository for each analytical chapter in this dissertation. Each chapter documents how tables were joined to create new datasets to test each hypothesis and fulfil each objective listed in Chapter 1. Further details are provided in each chapter. In this chapter, the ERD results were used to provide an exploratory summary regarding the collected data.

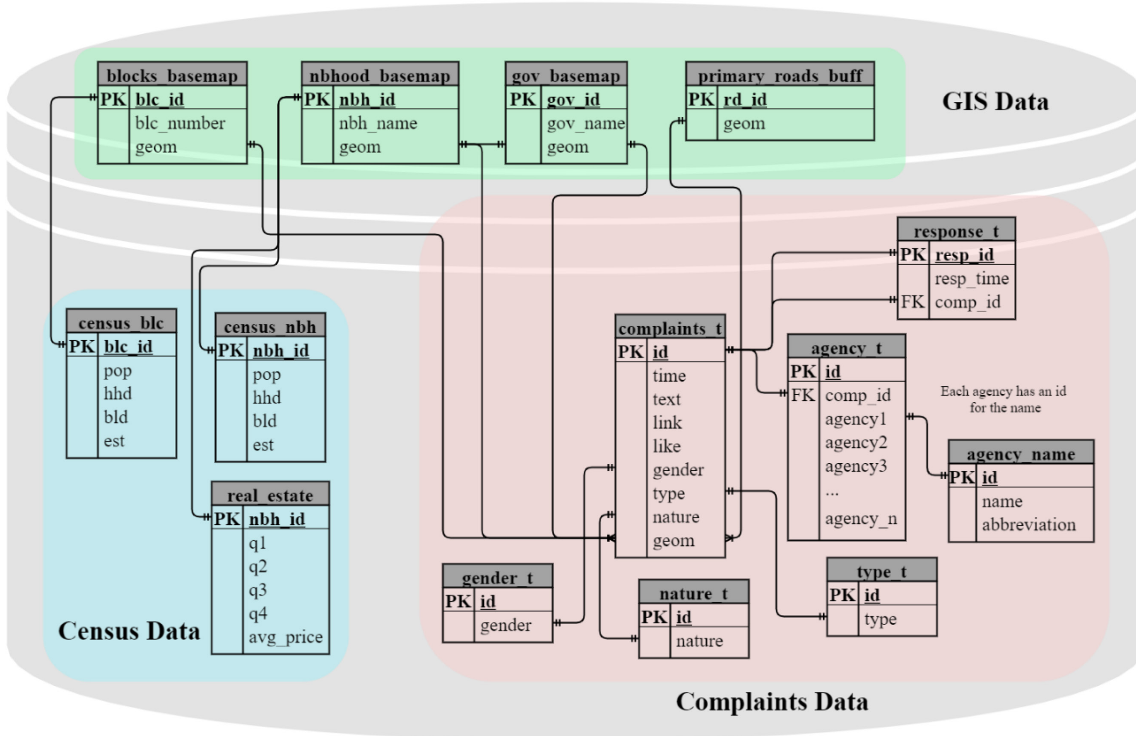


Figure 3.10. **Research main Entity Relationship Diagram (ERD).**

Citizen complaints data summary

After a successful web scraping process, a total of 6,257 posts were collected from the Q8needsyou account in 2019. After the data collection, the posts were generally classified into complaints (5,872 or ~94%) and non-complaints (385). Non-complaints are posts that do not include a report of an issue regarding the urban commons. An example is an acknowledgment of voluntary activity (e.g., beach cleaning). Another example includes resolved complaints. In such cases, complaint locations were already captured in the original post. Therefore, posts noting that complaints have been resolved were treated as non-complaints. Finally, a monthly report is usually shared regarding governmental responsiveness, and these reports were also classified as not containing complaints.

Concerning complaints, the data were classified into geographic (4,958) and non-geographic complaints (914). Non-geographic complaints are cases where a location was not indicated or identified, or complaints were agency-based and not connected to a single location (e.g., postal service delivery complaints). Also, there are cases where it was impossible to identify the location, such as speeding vehicles' complaints.

Next, geographic complaints were classified based on their spatial scale into neighborhood level (100), block level (106), street level (783), and approximate location level, which represents the most precise level (3,939). There are cases where the location can be classified at the neighborhood level, such as complaints at multiple streets (25). Also, some complaints are within Kuwait Bay (5) and were excluded from this dissertation's analysis. The overall taxonomy of citizen complaints in Kuwait is summarized in Figure 3.11.

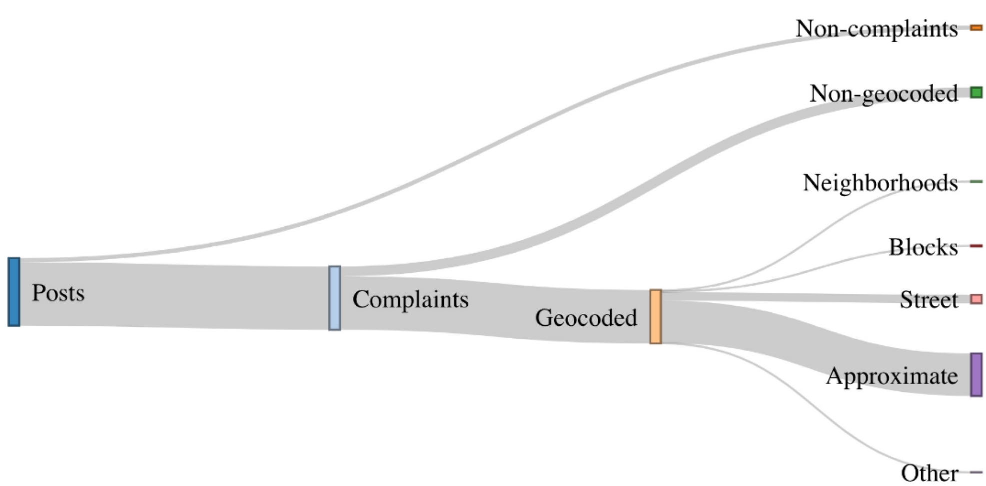


Figure 3.11. Taxonomy of citizen complaints in Kuwait.

As mentioned above, there were 4,958 geocoded complaints (79.2% of all posts) in Kuwait at multiple spatial scales. All geocoded complaints are presented on the maps in Figure 3.12. In Figure 3.12A, complaints are represented by a simple point symbol. However, due to large, clustered point samples, there is visual clutter on the map, and it becomes more complex to identify high or low clusters of complaints visually. In Figure 3.12B, complaints are visually rendered to highlight areas with higher existence of complaints. Areas with lighter shades reflect more complaints and vice versa. As perceived from the maps in Figure 3.12, the majority of complaints are within the metropolitan area.

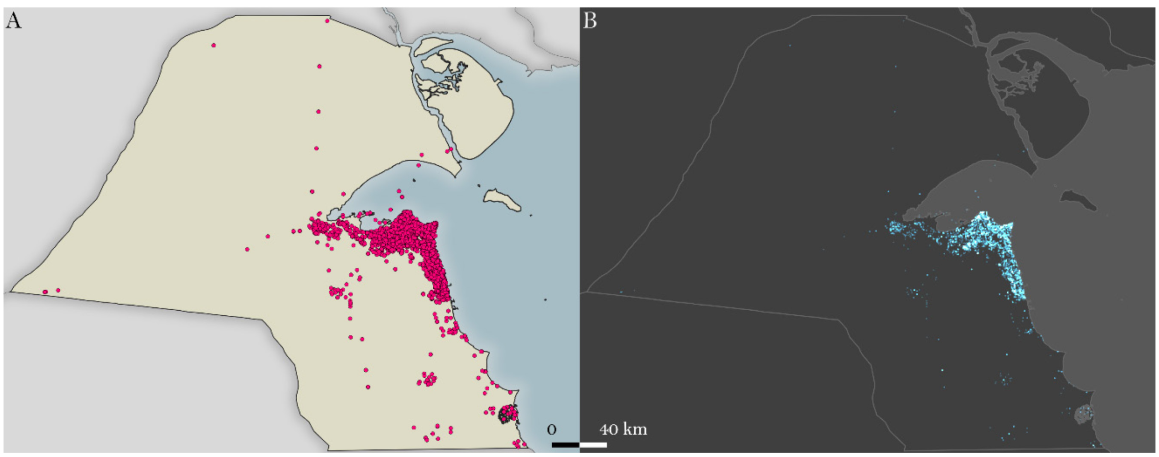


Figure 3.12. Geocoded complaints in Kuwait. Complaints were represented by simple point symbology (A), but high visual clutter exists. To reduce the visual cluttering, points were rendered (B) to highlight high or low cluster of complaints.

Based on complaint taxonomy and the spatial distribution of complaints, it is possible to perform spatial pattern analysis at the global (point pattern) and local (areal) levels. Also, aggregating the data to the neighborhood level results in a larger sample size for the analysis (since some complaints could only be coded to a neighborhood, and not to a precise point). Additionally, real estate prices were available at the neighborhood level only. Therefore, the research was set to be at the neighborhood level instead of the block. Further details on these choices are provided in conjunction with other analytical considerations in Chapters 4 and 5.

Using the timestamp of each post, the temporal distribution of the complaints is visualized in Figure 3.13.

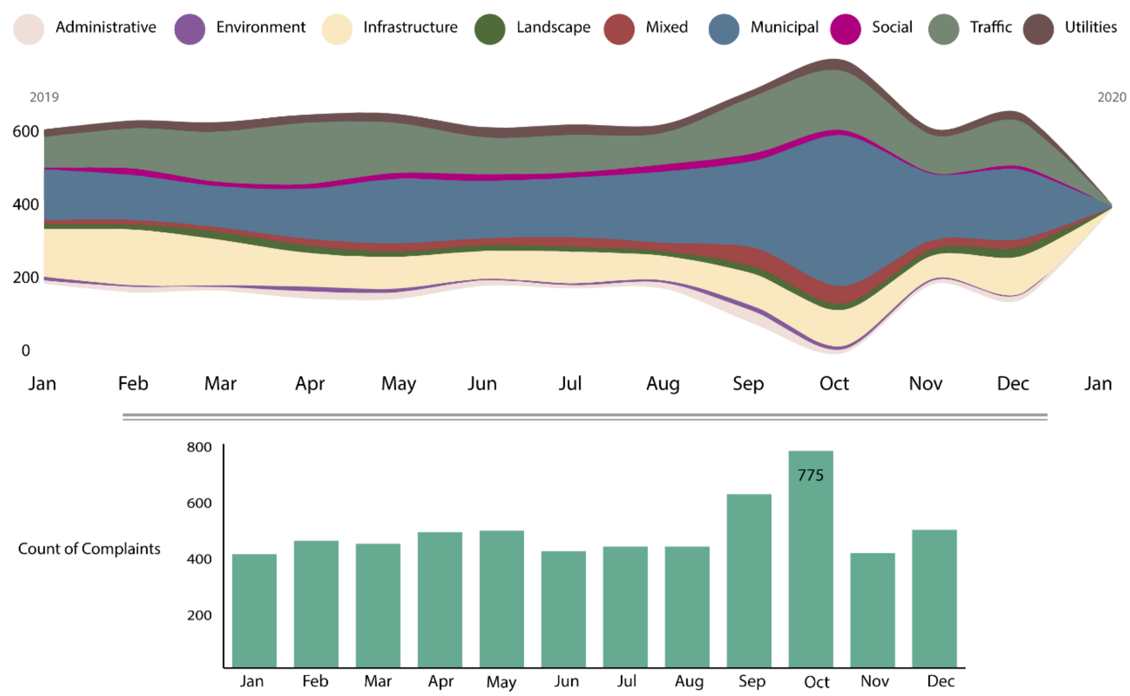


Figure 3.13. Complaint's volume on a monthly basis based on their type. The overall frequency of complaints is included at the bottom of the figure.

The preceding visualization includes the temporal volume of complaints based on their type (Figure 3.13 top) and the overall monthly frequency (Figure 3.13 bottom). Based on the inspected pattern, complaints tend to decrease during the summer and increase at the beginning of winter. Also, municipal complaints were the most frequent type, peaking in October. After municipal complaints, infrastructure and traffic complaints had the highest observed frequencies across Kuwait. Note, though, that certain types of complaints increase during specific times, while others are somewhat more constant. For instance, traffic complaints increase between March and April, while utility complaints exhibit less temporal variation.

Figure 3.14 visualizes the volume of agency tags in the posts (refer to Table 3.2 for agency codes). The most frequent agency tagged was the Municipality, with 2,666 posts. The Ministry of Interior and the Ministry of Public Works were mentioned 2,327 and 1,375 times, respectively. Agencies that provide services with less interaction with the public had a low frequency of complaints, such as Kuwait Oil Company or Kuwait Port Authority, with seven and five complaints, respectively. Surprisingly, some agencies that typically involve high levels of public interaction exhibited lower complaint counts, such as the Kuwait Public Transportation Company with only 24 complaints.

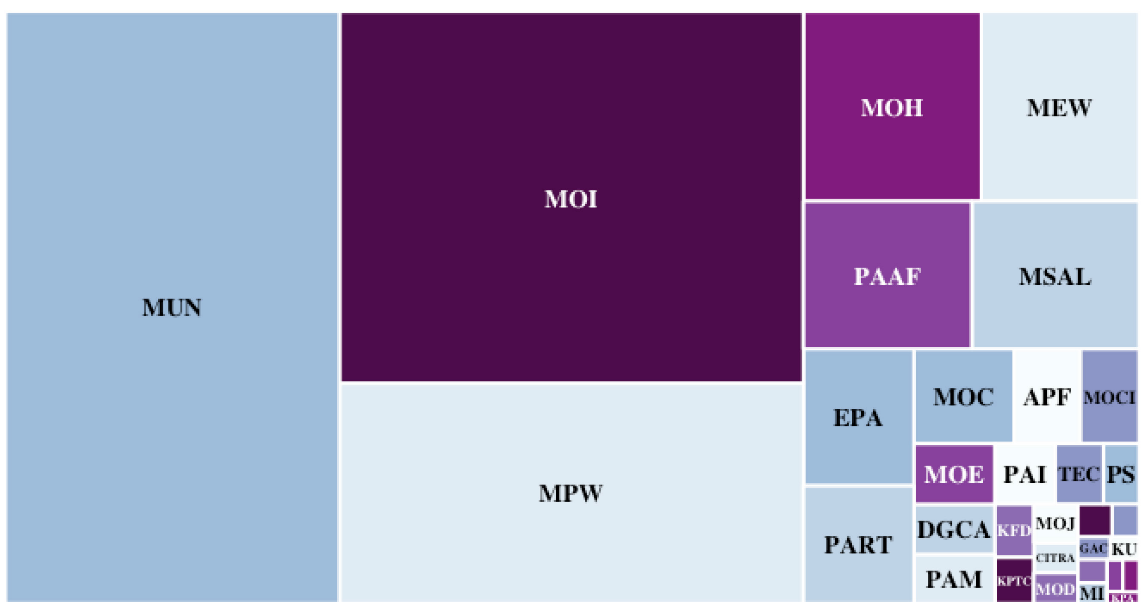


Figure 3.14. Agencies frequency treemap.

Consistent with the gender disparity in Instagram accounts noted above (with males constituting more than 61% of Instagram users), participation was significantly higher among males compared to females (Figure 3.15). At the same time, human-based complaints linked to incivilities or negative externalities occurred more frequently in 2019 than complaints on issues that occur through natural processes (e.g., sidewalk cracking). Breaking complaints out by both gender and nature of complaint yields the following: of 3,493 complaints with gender information, 3,117 (96.3%) were made by males, and about 69% of the male-based complaints dealt with human-based issues (2,153 complaints); females contributed 13.7% of the complaints (426) and, consistent with males, 79% (337) of complaints dealt with human-caused issues. Figure 3.15 summarizes these observations graphically.

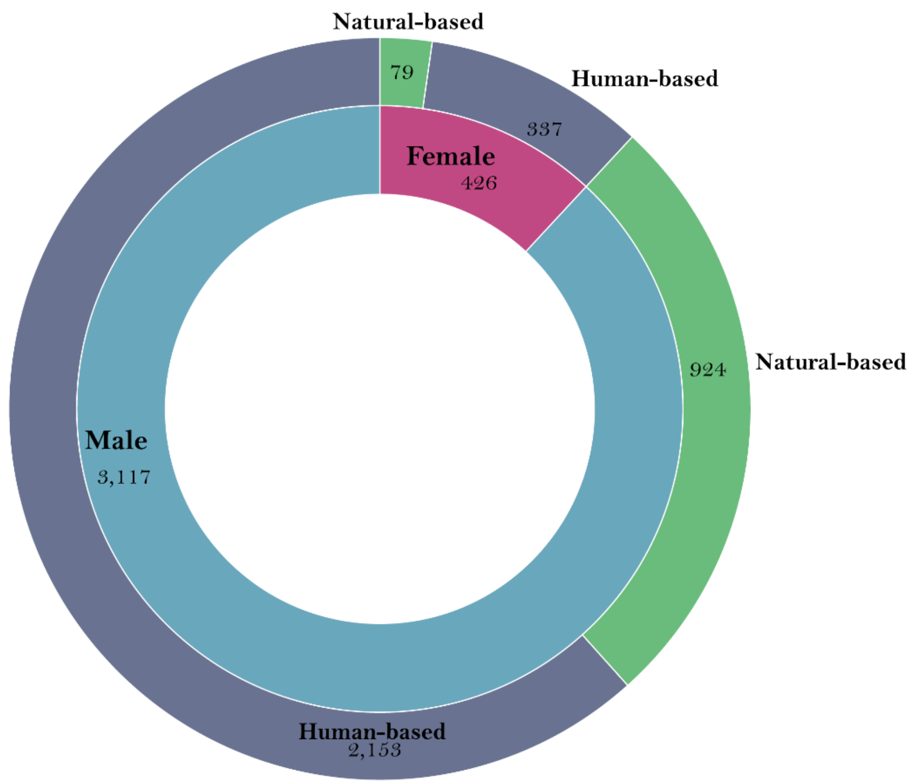


Figure 3.15. Complaints based on gender and nature.

With respect to engagement with posts, the highest observed engagement was 17,530, and the average number likes per post was 184. A statistical summary of engagement per complaint types is given in Table 3.3. Administrative complaints were associated with the highest engagement statistics. Despite having relatively few Administrative complaints (173), this finding suggests that citizens may have a higher propensity to share a specific type of complaint (e.g., Municipal), but they also may engage more with other types.

Table 3.3. Statistical summary of citizen engagement per complaint type.

Type	Max likes	Avg likes
Traffic	5456	207
Municipal	6345	157
Infrastructure	4102	157
Utilities	3942	168
Landscape	2087	170
Environment	1363	225
Social	776	212
Administrative	17530	401
Mixed	12146	236

Data uncertainty and limitations

All research projects that rely on SM are characterized by incompleteness (in that not all citizens have access to the technology or skills to use SM) and uncertainty (in that not all issues lead to complaints, and not all complaints are justified, among other concerns). On the backdrop of these general concerns, the total count of complaints made to the Q8needsyou Instagram account in 2019 was approximately 5,800. This sample is dependent on the followers of the Q8needsyou account. If users do not follow the account, they cannot report issues to it. Moreover, users who do follow the account represent only a portion of Kuwait society, given that not all citizens are necessarily aware that the account exists nor are all citizens Instagram account holders. On the 5th of October 2020, the number of Q8needsyou Instagram followers was ~102,000, which would account for about 2.2% Kuwait's population. With that in mind, it is clear that the SM account cannot be a centralized complaint system (like 311) on its own. Additional channels and options to engage all residents is clearly need. Nonetheless, because Kuwait does not currently have official online channels for receiving complaints, the Q8needsyou account is arguably the best option for the type of research conducted in this dissertation.

Building on this point, other than incomplete data on user gender, the SM data analysed herein do not contain information on a poster's socioeconomic characteristics, such as age, income, educational level, or technology usage, that would make it possible to understand personal attributes that contribute to complaint behavior and lead to participation in citizen-government interactions.

Another area of data uncertainty enters in the geocoding process. For this study, geocoding was done manually based on the location description included in each complaint. The location description depends heavily on a citizen's local knowledge and their tendency to share precise details. There were cases when reporters indicated that they shared detailed location specifications, but no details were found in the complaint. An example is presented in Figure 3.16. In this post, the user stated that "the location of the complaint is attached," but only the administrative level was indicated (i.e., block-level). Such a complaint could have a better locational precision if the user included detailed location instructions. This limitation reduces the sample size to be used in the global-level spatial point pattern analysis, because a precise point location is unavailable.

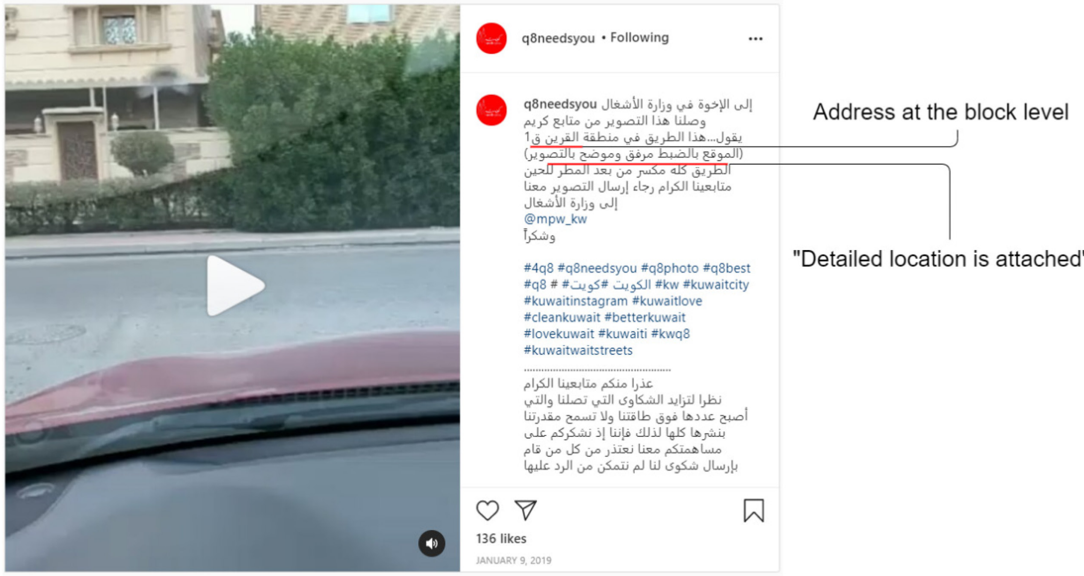


Figure 3.16. An example of geocoding limitation.

Additionally, the agency data mentioned in each complaint was based on the reporter's local knowledge. An SM user would identify the responsible agencies based on their assumption, and this may produce a false/negative result when analyzing the roles and interrelationships of agencies in responding to complaints. For instance, a citizen wondered if the water leakage in Figure 3.17 fell under the purview of Ministry of Public Works, the Ministry of Electricity and Water, or the Public Authority of Agriculture and Farming. Such information may falsely increase the association between several agencies. Such a case would be resolved if a 311-like centralized system existed in Kuwait, where government employees with bureaucratic knowledge determine the responsible agencies and assign complaints to those agencies.

Finally, the census data is from 2011, which was the last full census in Kuwait. The time difference between the complaints and census datasets is about a decade. When new census data become available, it will be important to replicate this research with the updated socioeconomic data to ensure that the findings reported below still hold.

Figure 3.17. An example of mentioning multiple agencies that may be associated with the complaint.

While the preceding challenges are important precautions for engaging in the type of work carried out in the remaining chapters, VGI citizen complaints are arguably the optimal information source for research on technology-based citizen-government interactions in areas where no 311 or 311-like system exists, such as Kuwait. On that note, the data described in Figure 3.10 were used to perform spatial analyses aimed at uncovering patterns of complaints and investigating links between complaint activity and demographic and socioeconomic attributes at the neighborhood level of analysis. Specific research questions, data, methods, results, discussions, and conclusions are provided in each of the next three chapters.

4. SPATIOTEMPORAL PATTERN ANALYSIS OF CITIZEN COMPLAINTS

Geographic pattern analysis is an essential step for understanding how geographic phenomena are distributed in a given study area, and for asking questions about the processes that might be generating those patterns. Pattern analysis is defined as the study of the spatial arrangements of point or polygon features in two-dimensional space (Chang 2018). Chang (2018) describes two levels of spatial pattern analysis: (1) a global level, where point patterns are judged to be random, dispersed, or clustered; and (2) a local level, where non-randomness in global patterns is traced to its sources (i.e., areas where values of the phenomenon of interest are significantly higher or lower than what would be expected by chance alone). At the global level, distance-based methods are regularly used to examine the point pattern. Two common distance-based methods are *Average Nearest Neighbour* (*ANN*) and *Ripley's K-function*. At the local level, a common method for detecting the locations of so-called "hot" or "cold" spots in a spatial distribution is the *Getis Ord Gi** statistic (Grekousis 2020).

Grounded in the literature review from in Chapter 2, and enabled by the data development in Chapter 3, this chapter examines global and local patterns of citizen complaints in Kuwait. Recalling that most studies of citizen complaints made to centralized 311 systems in U.S. cities find that complaints exhibit spatial clustering, this chapter evaluates whether complaints made to a volunteer-run social media (SM) account – in lieu of a governmental 311 system – are also clustered – or if they instead tend to be randomly distributed. More precisely, the chapter answers the following research questions and subquestions, which are arranged by scale (global and local):

Research Questions (Global)

1. (a) Is the annual distribution of citizen complaints characterized by spatial randomness?

   (b) Is each seasonal distribution (Spring, Summer, Fall, Winter) of citizen complaints characterized by spatial randomness?

2. (a) Is the annual distribution of citizen complaints from $type_i$ characterized by spatial randomness?

   (b) Is each seasonal distribution of citizen complaints from $type_i$ characterized by spatial randomness?

Research Questions (Local)

3. (a) Are there neighborhoods in Kuwait where annual complaint volumes are higher (lower) than what is expected by chance alone?

   (b) Are there neighborhoods in Kuwait where seasonal complaint volumes are higher (lower) than what is expected by chance alone?

4. (a) Are there neighborhoods in Kuwait where annual complaint volumes from $type_i$ are higher (lower) than what is expected by chance alone?

   (b) Are there neighborhoods in Kuwait where seasonal complaint volumes from $type_i$ are higher (lower) than what is expected by chance alone?

where $type_i$ represents one of the two most frequent types of complaints (see the data and methodology section below).

The overarching null hypothesis under investigation is therefore:

H_0: Spatial patterns of citizen complaints are random.

Testing this hypothesis using global and local statistics will reveal whether SM complaint patterns tend toward clustering like in the case of 311 patterns; and, if so, where concentrations of atypically high or low complaint activity occurs in Kuwait. The next section describes the structure of the data used for these purposes, drawing on the main Entity Relationship Diagram (ERD) presented in Chapter 3 (Figure 3.10). It then describes the methods employed to answer each of the preceding research questions. Following an explication of the results, the chapter concludes by discussing and interpreting the main findings relative to the literature reviewed in Chapter 2. At bottom, consistent with existing research on 311 systems, I find that citizen complaints in Kuwait exhibit spatial clustering, with high concentrations of complaints occurring nearer to the urban center.

Data and methods

Several tables listed in the main ERD for this project (Figure 3.10) are needed to facilitate point pattern and cluster analyses of citizen complaints. The list of tables included the “complaints_t,” “type_t,” “census,” and Geographic Information System (GIS) layers (“metropolitan area,” “major roads,” and “neighborhoods”). From each table, specific columns were selected to create an ERD for conducting cluster analyses. The GIS tables were selected to choose the complaints that are relevant to the four groups of research questions listed above. Census data were used to get the total population for each neighborhood in order to convert raw complaint counts into rates (for purposes of data normalization). The type of each complaint was coded in the “complaints_t” table (e.g., “municipal” type has 2 as a code integer). The “type_t” table stored the type name as a string and was used to identify the most frequent types and for statistical summaries.

Regarding the GIS data, all layers were reprojected to the local projected coordinate system for Kuwait (KUDAMS/KTM EPSG:31901). Figure 4.1 illustrates the overall ERD designed for this chapter.

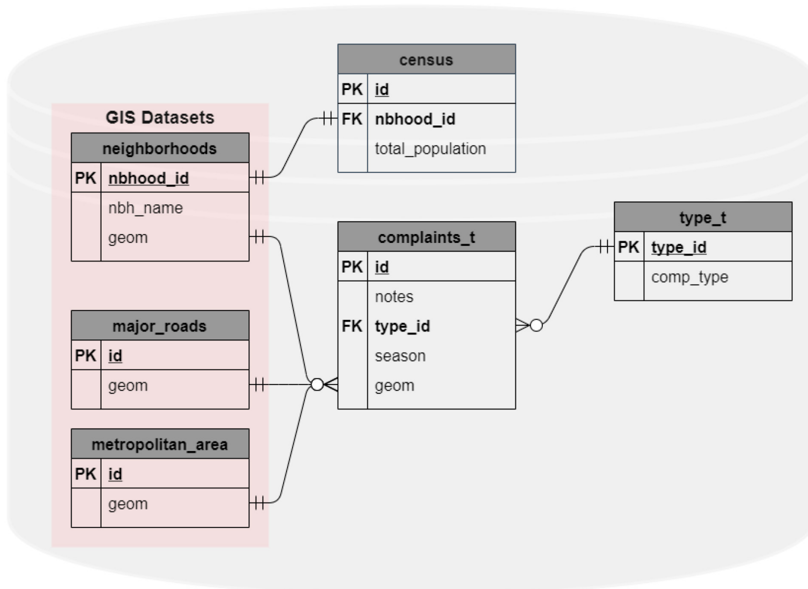


Figure 4.1. Overall ERD used for chapter 4 research questions.

The GIS datasets were joined with the “complaints_t” table via a one to many (1:M) relationship using the geom field, where each complaint occurs on one geometry feature, and a geometry feature can contain many complaints. Census data have one to one (1:1) relationship with the “neighborhoods” table using the neighborhood_id field. Finally, “complaints_t” has a (1:M) relationship with the “type_t” since each complaint is assigned one type, and one type can be assigned to many complaint types.

Building on the tables shown in Figure 4.1, the data used in this chapter were selected based on specific criteria to answer each research question. The diagram in Figure 4.2 illustrates the criteria of the data used for research questions 1 and 2. The complaints in this analysis must be at the highest spatial scale as much as possible.

Therefore, aggregated complaints (e.g., at the neighborhood level) will be excluded from the final table for the analysis. To accomplish that, the following conditions were used to select the required complaints for research questions 1 and 2:

A. Complaints that are within the metropolitan area.
B. Complaints for which relatively precise point locations are available.
C. Complaints that are not within the major roads buffer zone.
D. Complaints that are not a “traffic” type.

The reason for omitting “traffic” complaints is related to the difficulties of geocoding most of the traffic-related complaints (such as speeding or dangerous driving behavior). As mentioned in Chapter 3, linear road features often cross through multiple administrative units. When complaints report only a road name, it is unclear where on the road the problem occurred. Moreover, traffic issues like speeding are, by definition, temporary and removed from the affected place as soon as the speeding vehicle exits the vicinity of the infraction. For these reasons, such complaints were omitted from the query, resulting in an analytical sample that is a subset of the total sample of geocoded complaints (refer to Chapter 3).

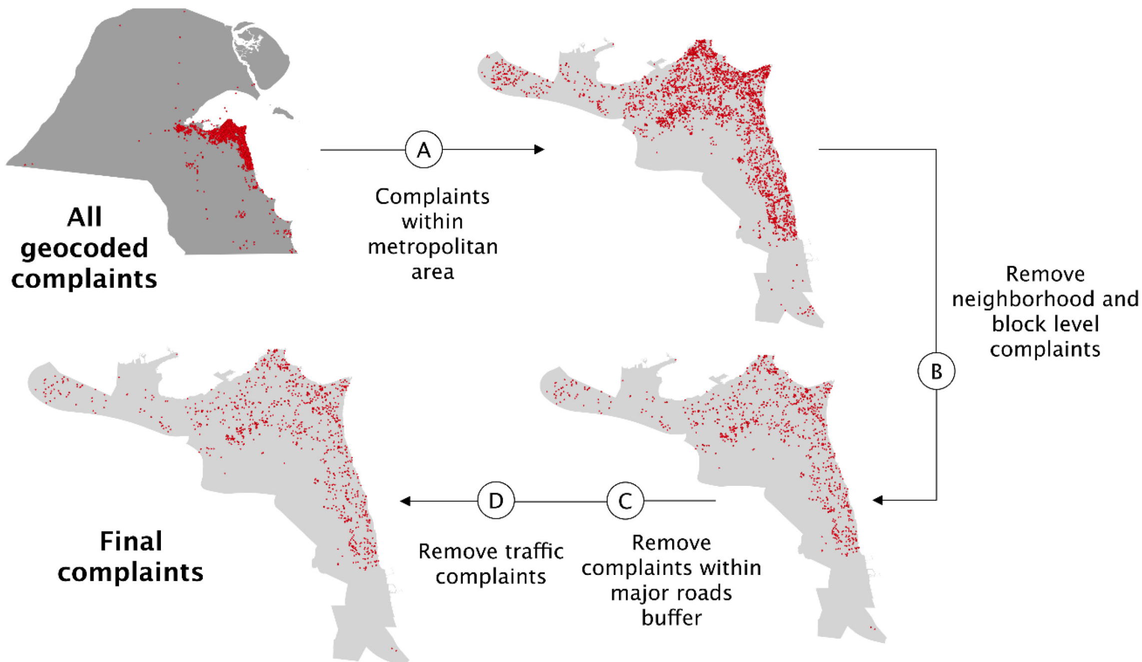


Figure 4.2. The data selection process for research questions 1 and 2. Further details are described in the text.

At this point, complaints within the metropolitan area with both type and season information were prepared to answer research question 1a. For the seasonal analysis in research question 1b, the data can be filtered to only include $season_i$. The same approach can be implemented for research question 2 by filtering the data to the selected type and season.

Regarding research questions 3 and 4, in order to identify the locations of hot- or cold-spot neighborhoods, complaints must be aggregated to the neighborhood level of analysis. Therefore, the criteria for research questions 3 and 4 are:

A. Complaints are within the metropolitan area.

B. Complaints are not within the major roads buffer zone.

C. Complaints are not a "traffic" type.

D. Complaints that lie within neighborhood boundaries and are aggregated thereto.

The output table includes the count of complaints in neighborhood$_i$. For normalization, the count of complaints was divided by the total population from the census 2011 for neighborhood$_i$, then multiplied by 1,000 to get the count of complaints per 1,000 residents, similar to the use of infection, birth, and death rates in public health. Normalized complaints were calculated for all combinations of type$_i$ and season$_i$ under investigation. The data filtering process for research questions 3 and 4 is illustrated in Figure 4.3. An equivalent procedure was used for type and season classification.

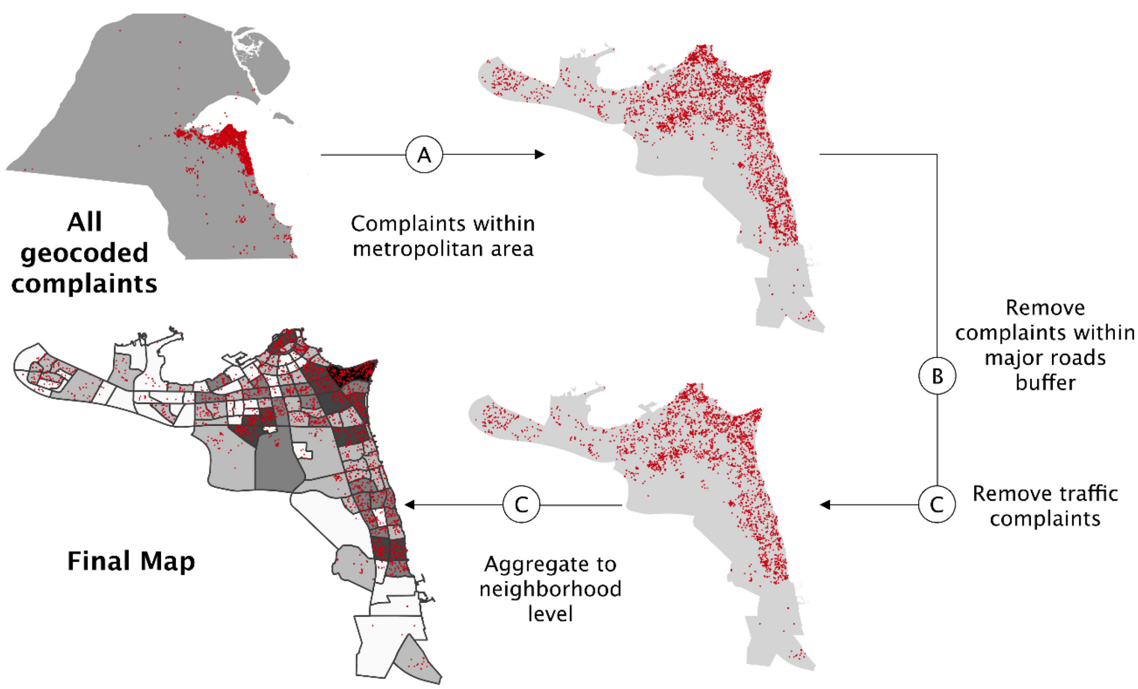


Figure 4.3. The data selection process for research questions 3 and 4. Further details are described in the text. The final thematic map in the figure is for illustration purposes. The detailed thematic maps are presented in the results section.

Regarding the global-level analysis, both *ANN* and *Ripley's k-function* from Esri ArcGIS Pro were used to evaluate complaint patterns for evidence of global clustering. *ANN* is a statistical test used to characterize a point pattern (ESRI 2020a). It is calculated as:

$$ANN = \frac{\bar{D}_O}{\bar{D}_E} \quad (4.1)$$

where $\bar{D}_O$ is the observed mean distance between each point and its nearest neighbor, and it is calculated using the following equation:

$$\bar{D}_O = \frac{\sum_{i=1}^{n} d_i}{n} \quad (4.2)$$

and $\bar{D}_E$ is the expected mean distance for the point given in a random pattern:

$$\bar{D}_E = \frac{0.5}{\sqrt{n^2/A}} \quad (4.3)$$

d_i in Equation (4.2) is the distance between $point_i$ and its nearest neighbor. A is the area of the minimum bounding box around all points. When the *ANN* index value is less than one, the point pattern exhibits clustering. If the index is greater than one, it exhibits dispersion. Values near zero indicate random distributions. While *ANN* is useful for quickly summarizing the type of pattern under investigation – i.e., random, clustered, or dispersed – it is sensitive to boundary issues, among other limitations (Grekousis 2020). As such, it is rarely the case that *ANN* is used as a standalone method for evaluating point patterns.

With that in mind, *Ripley's k-function* takes into account multiple incremented distances for $point_i$ (ESRI 2020b), allowing for a more nuanced understanding of pattern characteristics (i.e., it allows an analyst to evaluate whether clustering occurs only over small distances within the distribution or more broadly). The *k-function* is calculated using the following equation:

$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} k_{i,j}}{\pi n(n-1)}} \tag{4.4}$$

where d is the distance, A represents the total area of the features, and $k_{i,j}$ is the weight, which equals one if edge corrections are not applied. The results are plotted in a line graph. If the observed *K* value is greater than the expected *K* value for a particular distance, then the distribution is clustered at that difference. If the opposite holds, the pattern is dispersed. Through random permutation, it is possible to generate a confidence envelope around the expected *K* function. When an observed *K* value falls outside of that envelope, spatial clustering (*K* falls above the upper bound) or dispersion (*K* falls below the lower bound) is statistically different from what would be expected by chance alone.

Together, *ANN* and *Ripley's K* analyses can be used to answer research questions 1 and 2. Figure 4.4 shows the flow of these analyses for this chapter.

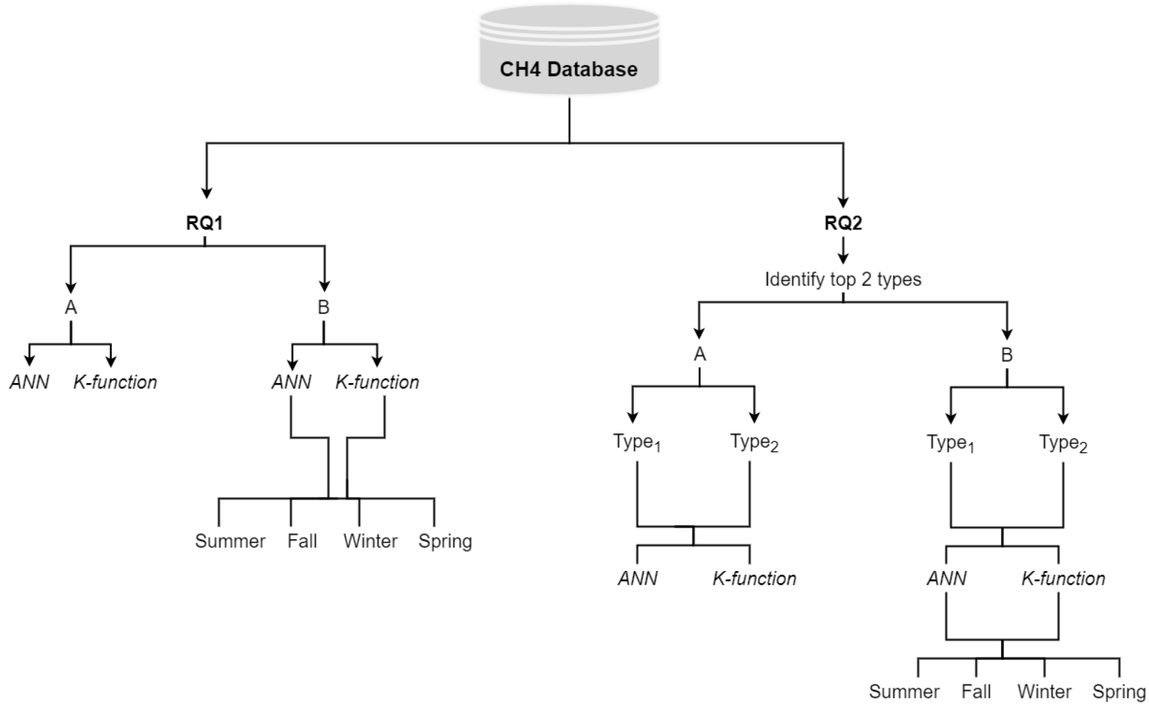


Figure 4.4. Research questions 1 and 2 analysis chart.

For research questions 3 and 4, the Getis-Ord G_i* was used to detect the presence and location of high or low clusters of neighborhood complaint rates. The open source software package GeoDa (Luc Anselin 2019) was used in these analyses. In brief, the G_i* statistic consists of a ratio of the weighted average of the values in a given neighborhood's neighboring locations to the sum of all values, including the value at the given neighborhood location (x_i). (Note: this "ego" value is not included in the alternative G_i statistic, which is the fundamental difference between the two variants of the Getis-Ord statistic.) G_i* is calculated as:

$$G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_j x_j} \tag{4.5}$$

This equation was applied to complaint rates at the neighborhood level for all of the complaint type and seasonal combinations of interest to research questions 3 and 4. Figure 4.5 shows the flow of these analyses for this chapter.

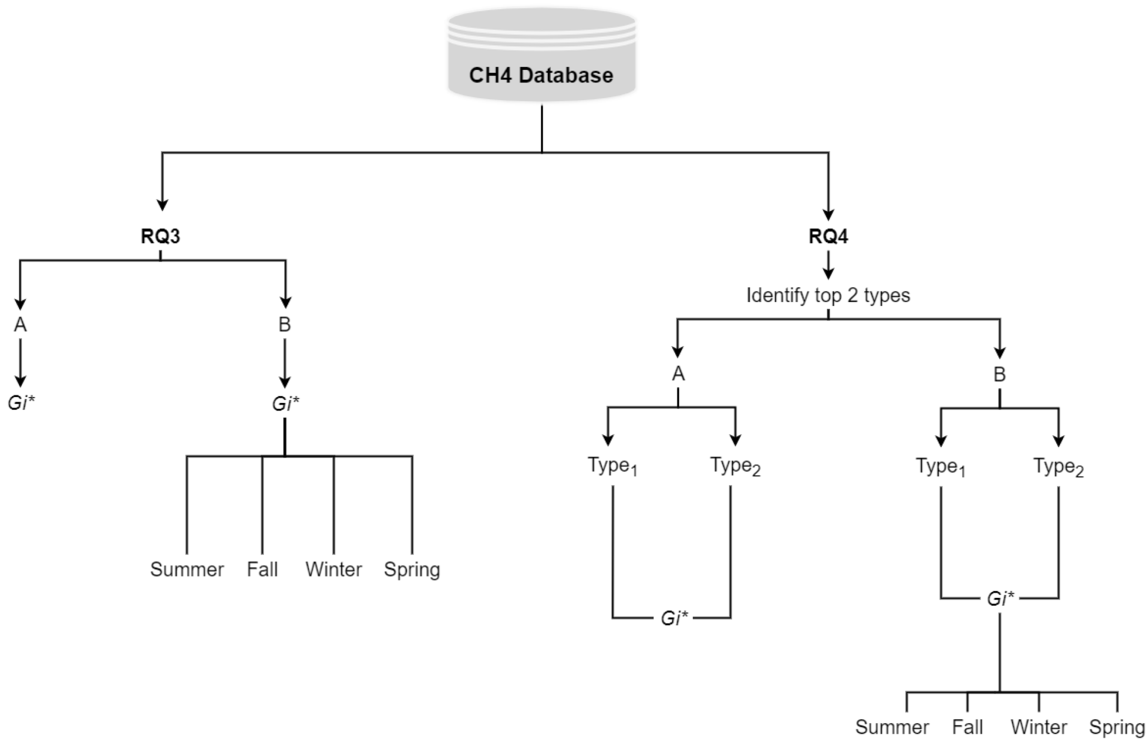


Figure 4.5. Research questions 3 and 4 analysis chart.

Results

Complaint distributions in space and time

After selecting the complaints that match the criteria laid out in research questions 1 and 2, the number of complaints available for global point pattern analysis was 1,256 out of 4,958 geocoded complaints (25.3%). The spatial distribution of the total set of these complaints, in the metropolitan area, is presented in Figure 4.6. Within this sample, the highest frequency of complaints occurred in the fall (403 complaints, or 32.1% of the total). The fewest complaints were recorded in the summer (194, or 15.5% of complaints). The seasonal frequency of complaints is illustrated in Figure 4.7, and the spatial distributions of complaints by season are mapped in Figure 4.8.

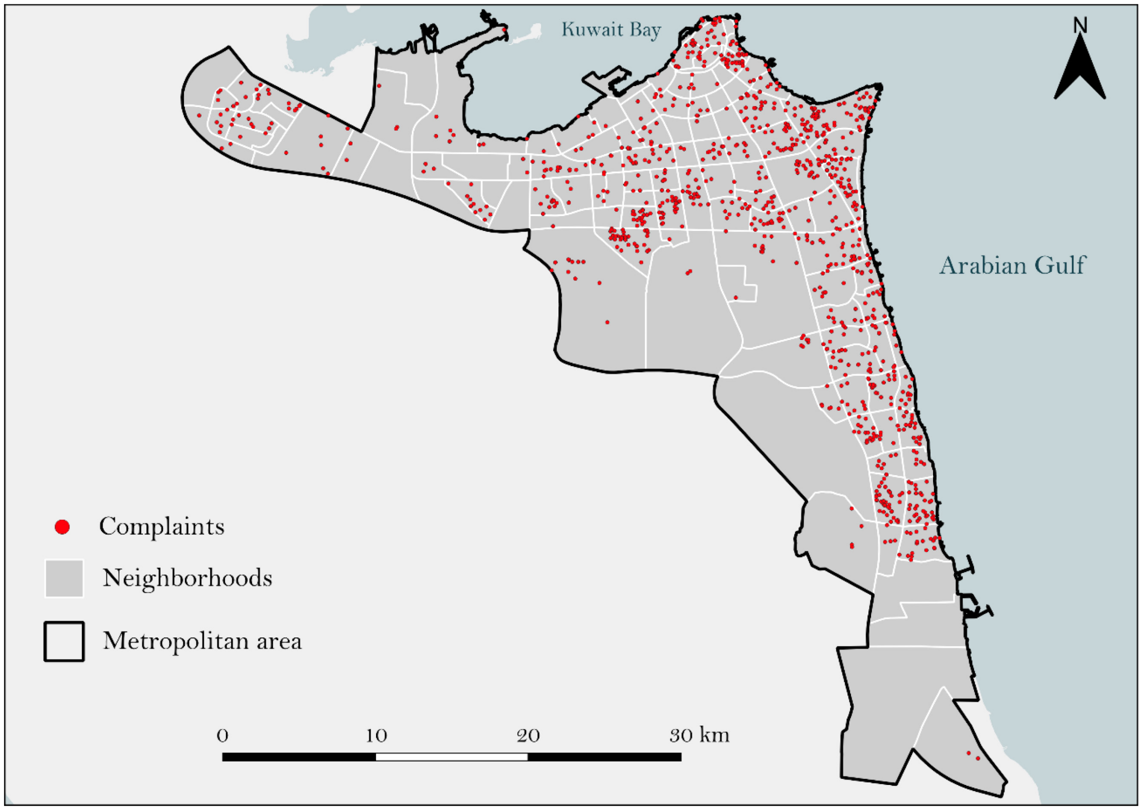


Figure 4.6. Research question 1a complaints' spatial distribution.

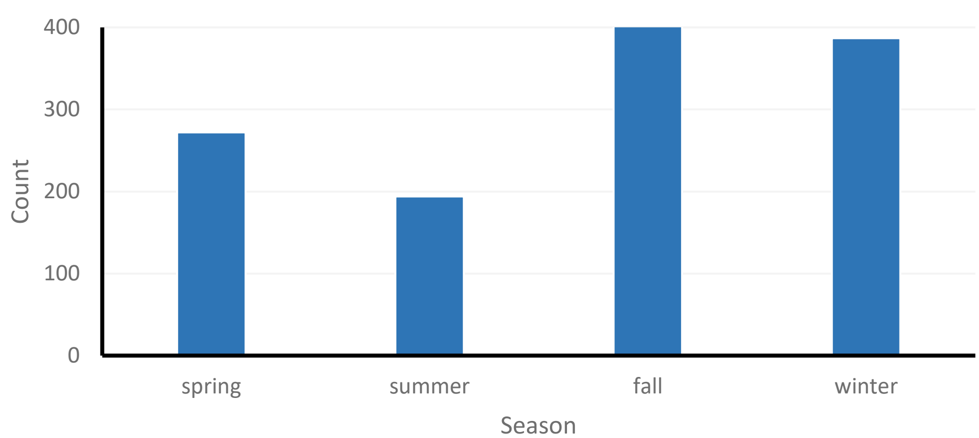


Figure 4.7. Research question 1b complaints seasonal frequency.

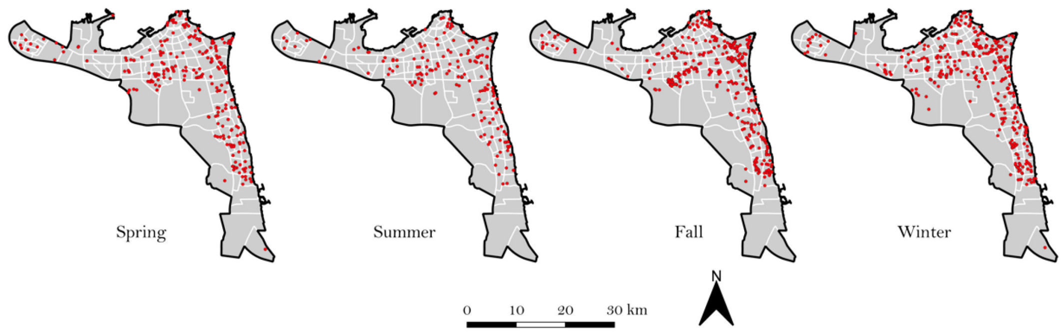


Figure 4.8. Research question 1b complaints spatial distribution for each season.

For research question 2, *ANN* was applied for the top two most frequent complaint types as a means to study spatial patterns by type – but in recognition that analyzing each individual complaint type would prove costly and distract from the main research objectives. On that backdrop, the frequency of complaints by type is shown in Table 4.1. Recall from above that "traffic" complaints were excluded from the analysis. Drawing on the information from Table 4.1, Municipal (hereafter "mun"), and Infrastructure (hereafter "inf") types were used in the analysis as a pilot means for testing whether spatial patterns are markedly different by type. The annual spatial distributions of these two types of complaints are shown in Figure 4.9.

Table 4.1. Research question 2 complaint types' frequency.

Complaint type	**Count**	**Percentage**
Municipal	690	54.9
Infrastructure	375	29.9
Utilities	64	5.1
Mixed	60	4.8
Landscape	46	3.7
Social	14	1.1
Administrative	4	0.3
Environment	3	0.2

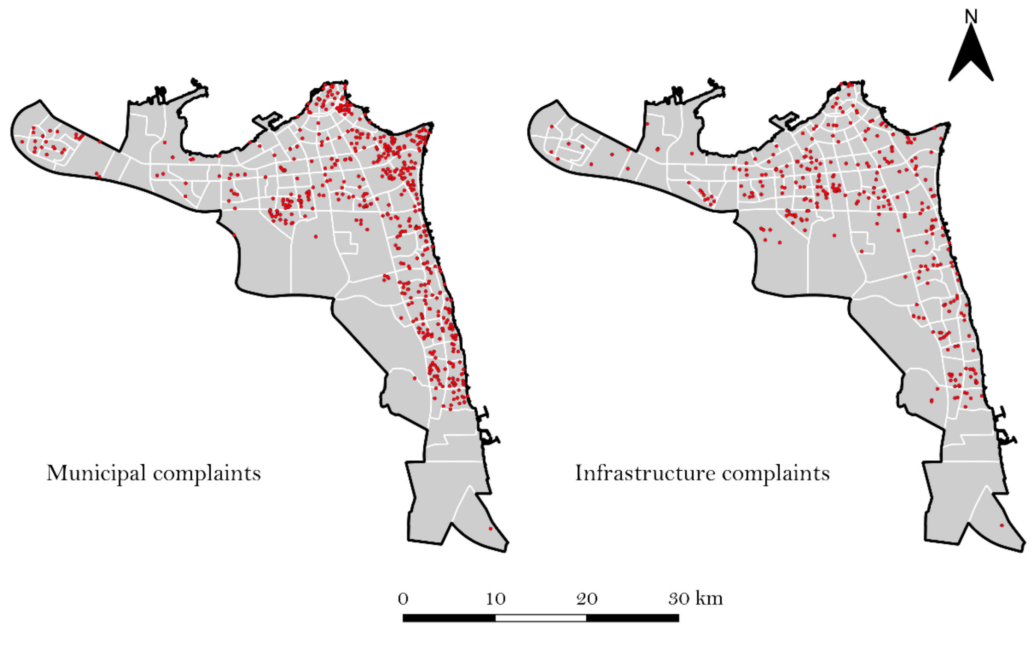


Figure 4.9. Research question 2a complaints spatial distribution based on the top two types.

For each type, point pattern analysis was performed first for the annual distribution and then again for each season, separately. Regarding the seasonal frequency for research question 2b, the maximum count of mun complaints occurred in fall, with 261 complaints (37.8%); whereas the inf category had a maximum count in winter, with 171 complaints (45.6%). The minimum count of complaints for mun and inf both came in summer, with 120 (17.4%) and 40 (10.7%), respectively. The seasonal frequency of the complaint types is presented in Figure 4.10. The spatial distributions of the complaints, by type and season, are mapped in Figure 4.11.

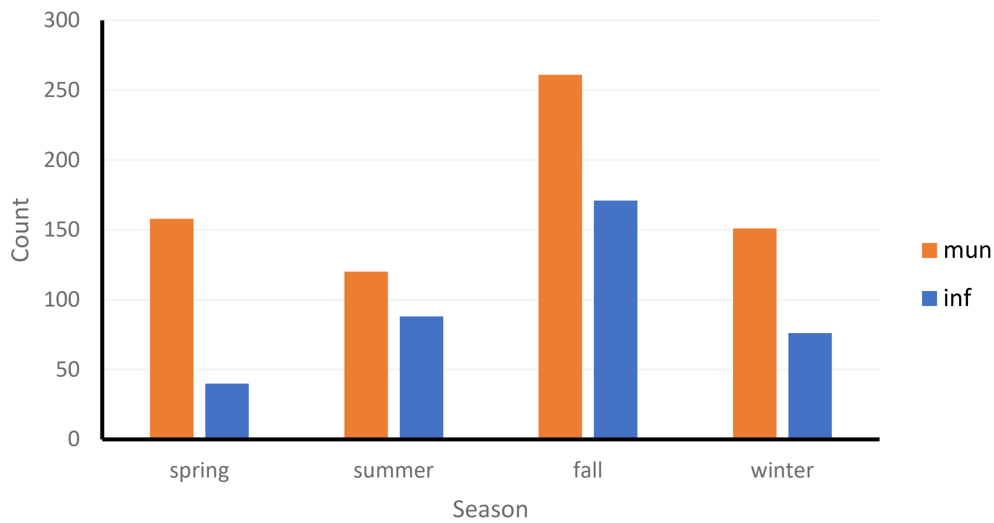


Figure 4.10. Research question 2b complaints seasonal frequency by type.

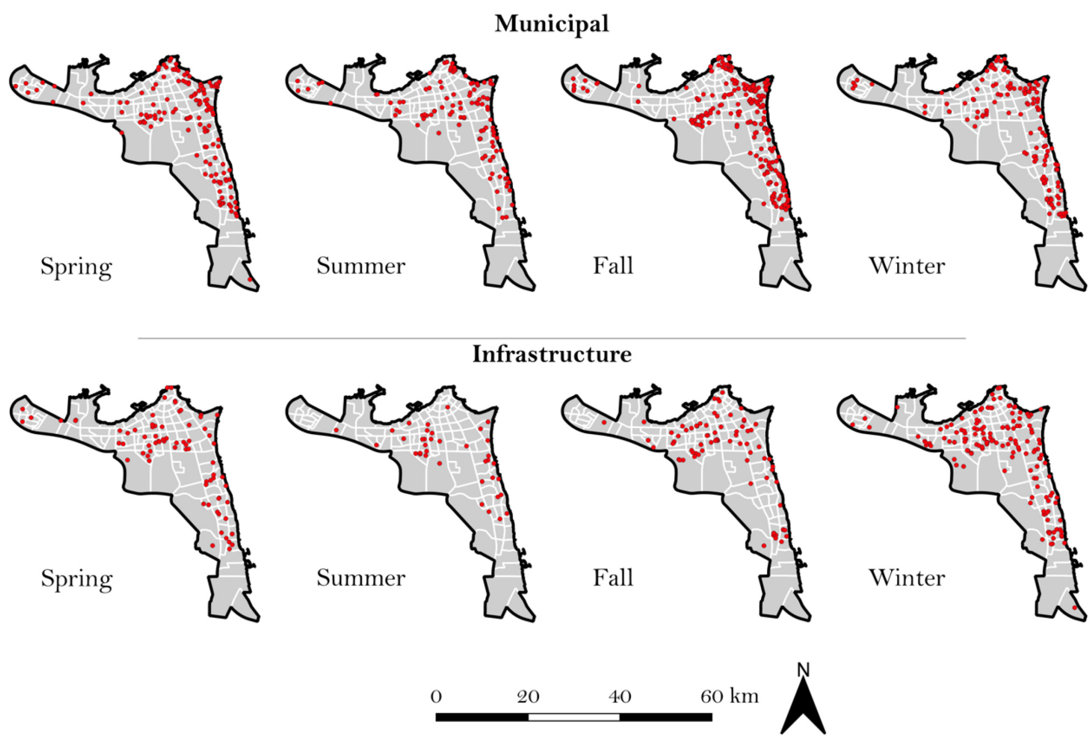


Figure 4.11. Research question 2b complaints spatial distribution based on the top two types for each season.

Average Nearest Neighbor results

ANN was applied to the distributions described in the prior section to answer all parts of research questions 1 and 2. The results of the analysis for research question 1 are summarized in Table 4.2. Based on the results, the complaints exhibited a clustered pattern both for the full year (question 1a) and during each season (question 1b). Therefore, I reject the null hypothesis that SM complaints in Kuwait are randomly distributed.

Table 4.2. Summary of the ANN results for research question 1.

Research question	OMD	EMD	NNI	z-score	p-value	SP
1a	210.7	4.3.5	0.52	-32.41	0.000	Clustered
1b spring	583.1	867.2	0.67	-10.3	0.000	Clustered
1b summer	627.5	1026.8	0.61	-10.4	0.000	Clustered
1b fall	354.6	712.4	0.5	-19.3	0.000	Clustered
1b winter	448.5	727	0.62	-14.4	0.000	Clustered

OMD = Observed Mean Distance, EMD = Expected Mean Distance, NNI = Nearest Neighbor Index, SP = Spatial Pattern.

Regarding research question 2, *ANN* was carried out for all of the complaint-type season distributions characterized in Figure 4.9 and 4.11 above. The results are summarized in Table 4.3. Coinciding with the findings for the total set of complaints (Table 4.2), the selected types of complaints exhibited clustered patterns when looking both at the full year of data (question 2a) and breaking complaints out by season (question 2b). Therefore, I reject the null hypothesis that the complaints are randomly distributed at all seasons and during each season separately for both types. This result is fairly intuitive, insofar as the distributions of the most frequent complaints should bear some resemblance to the distributions of all complaints, given the former's influence on the latter. In that sense, breaking complaints out by type is arguably more important for local rather than global analysis.

Table 4.3. Summary of the ANN results for research question 2.

Research question			OMD	EMD	NNI	z-score	p-value	SP
2a		Mun	277.6	544.5	0.51	-24.6	0.000	Clustered
		Inf	210.7	403.6	0.52	-32.4	0.000	Clustered
2b	mun	Spring	797.9	1137.8	0.7	-7.2	0.000	Clustered
		Summer	781.9	1305.6	0.6	-8.4	0.000	Clustered
		Fall	432.6	885.3	0.49	-15.8	0.000	Clustered
		Winter	639	1163.9	0.55	-10.6	0.000	Clustered
2b	inf	Spring	1159.7	1640.6	0.71	-4.9	0.000	Clustered
		Summer	1899.7	2261.4	0.84	-1.9	0.053	Clustered*
		Fall	969.1	1524.6	0.64	-6.5	0.000	Clustered
		Winter	752.2	1093.7	0.69	-7.8	0.000	Clustered

*Significant at 0.1

K-function results

Prior to presenting and interpreting K-function results, it is helpful to first note that the analysis depends on distance thresholds. In applications of Ripley's K-function, it is common to use 10 distance bands, which is somewhat arbitrary but generally sufficient to characterize the nature of spatial dependence within a geographic distribution (ESRI 2020b). For this chapter, analyses were carried out in Esri ArcGIS Pro using a maximum distance threshold equal to 25% of the maximum extent length of a minimum enclosing rectangle around all the points (i.e., complaints) in the distribution (ESRI 2020b).

To illustrate, Figure 4.12 shows a minimum enclosing rectangle for the complaints data with its x- and y-extents specified (51 km and 48.5 km respectively). The maximum length was found to be 51 km, and 25% of 51 km is 12.75 km. Using an approach recommended by Esri (2020b), based on these measurements, a distance increment of 12.75/10, or 1.75 km, was employed in the analysis of the full complaint data set shown in Figure 4.12. Equivalent procedures were used for all of the complaint data subsets used to fully grapple with research questions 1 and 2.

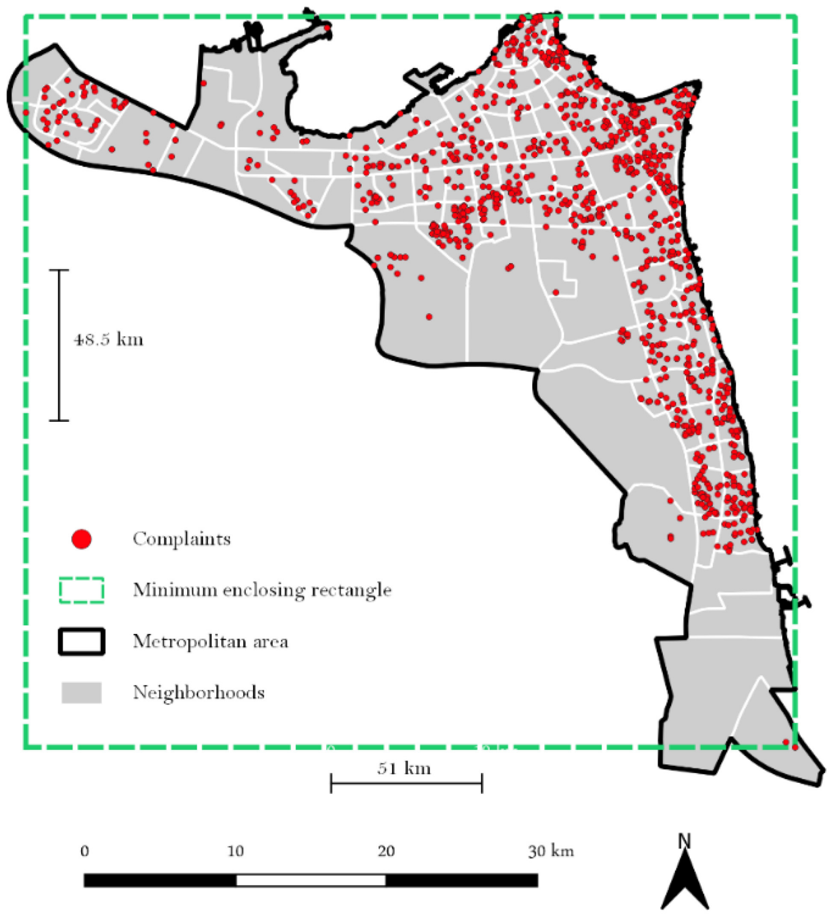


Figure 4.12. K-function distance calculation illustrative example.

The results from analyzing research question 1a with Ripley's K-function are presented in Figure 4.13. Based on the pattern of the observed curve, the points are clustered through the sixth distance band. In other words, complaints are clustered at near distances, but the pattern tends toward dispersion at far distances. This latter tendency is perhaps an effect of how relatively evenly spaced blocks (and, hence, residential areas) are throughout Kuwait (refer to Figure 3.5). Put another way, similar to how students tasked with drawing a random pattern on a grid attempt to ensure that each grid cell receives a point (thereby rendering the pattern nonrandom and overdispersed, since any given point's location takes into account the prior points' locations), the block-level geographies of Kuwait make it such that, over large distances, every "grid cell" will "receive a point" – leading to some dispersion at large distance bands (e.g., (Rogerson 2019). For that reason, the clustering that takes shape over near and moderate distances is arguably the stronger tendency, which supports the ANN finding that the global complaint pattern is clustered (Table 4.2).

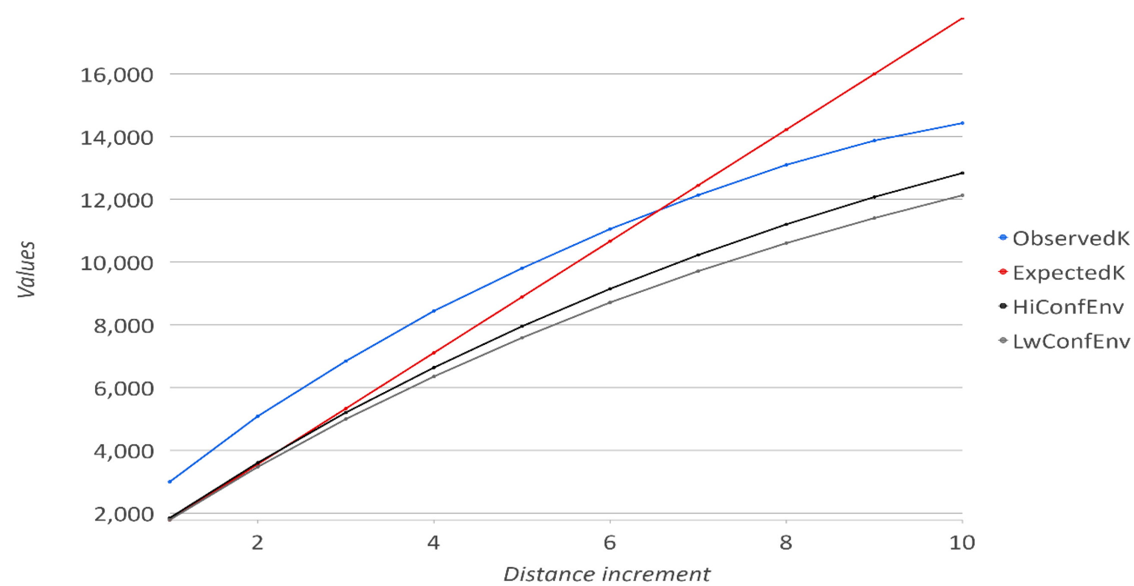


Figure 4.13. Research question 1a K-function results.

With respect to research question 1b, essentially the same qualitative patterns presented in Figure 4.13 were observed when complaints were broken out by season (Figure 4.14). As such, and in conjunction with the ANN analysis from above, it is possible to conclude that seasonal complaint patterns exhibit clustering.

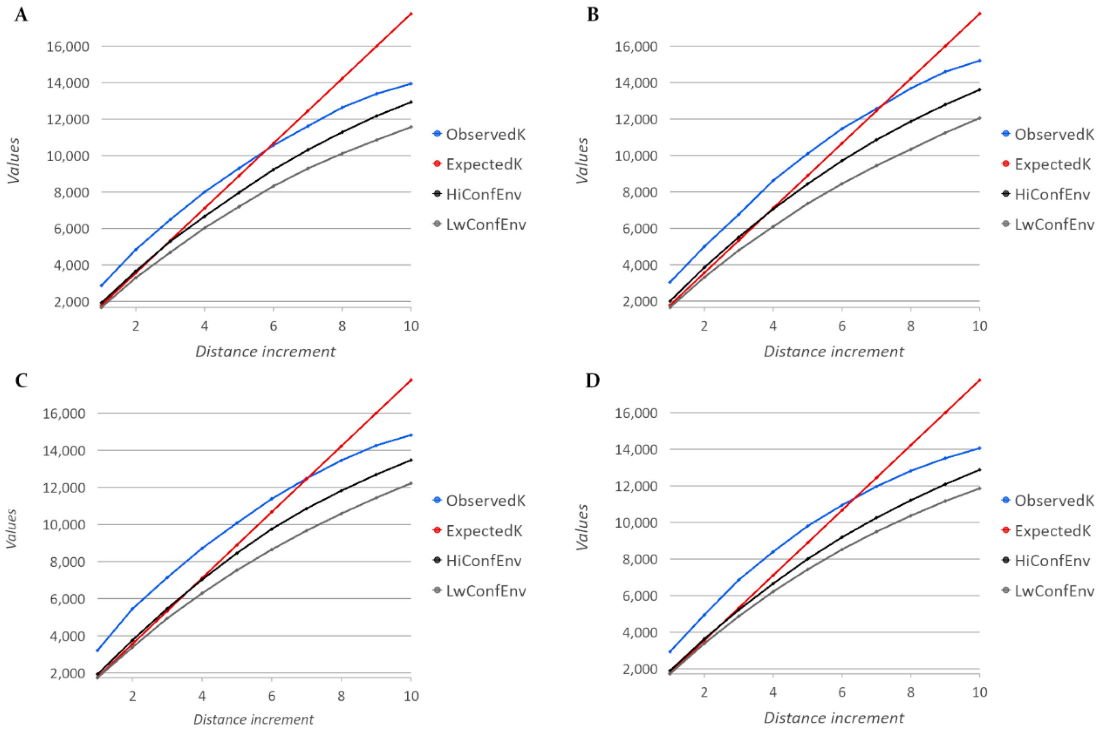


Figure 4.14. Research question 1b K-function results. (A) spring, (B) summer, (C) fall, and (D) winter.

Findings for research question 2a are shown in Figure 4.15. Once again, the patterns show significant evidence of clustering at near and moderate distance, with a tendency toward dispersion at large distances.

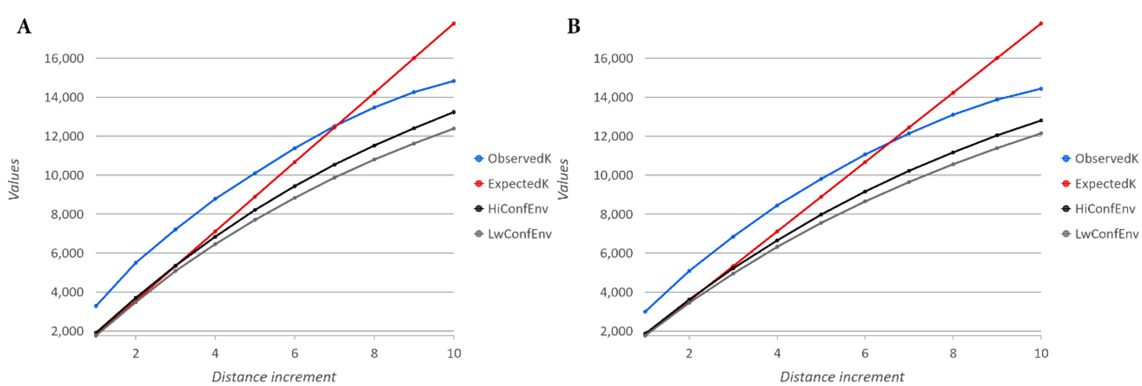


Figure 4.15. Research question 2a K-function results. (A) mun and (B) inf.

The results from analyzing research question 2b are displayed in Figures 4.16 (mun) and 4.17 (inf), respectively. In both cases, all seasons exhibited a clustered pattern near the 6th and 7th distance increment, just as in the prior results. As was the case above, the global similarity in the patterns of all complaints and of the two highest-frequency types of complaints is not surprising – recall that one weakness with global statistics is that they do not identify precise locations that have atypical values of the variable of interest. Local statistics, then, should be more useful for exploring differences within patterns by complaint type (see below).

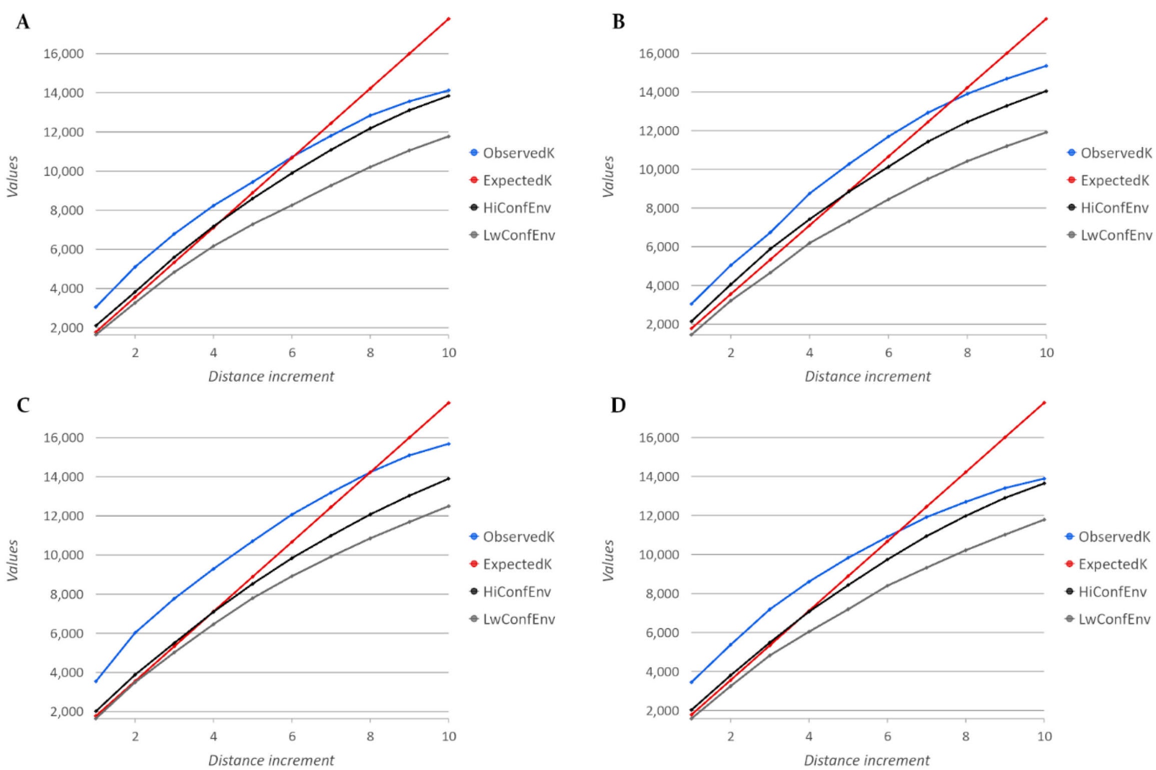


Figure 4.16. Research question 2b K-function results of the mun type. (A) spring, (B) summer, (C) fall, and (D) winter.

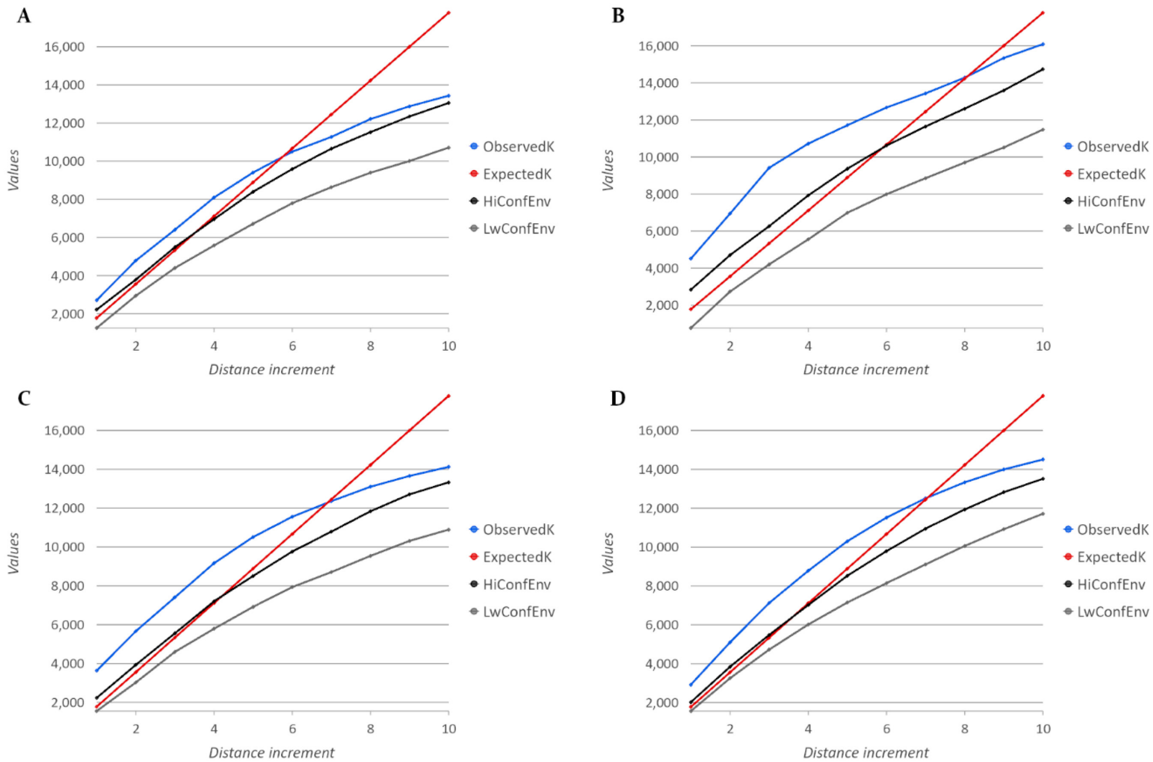


Figure 4.17. Research question 2b K-function results of the inf type. (A) spring, (B) summer, (C) fall, and (D) winter.

To summarize, all K-functions revealed clustered patterns of complaints over short to moderate distances. Combined with the unambiguous ANN results, there is ample evidence to reject the null hypothesis that complaints are randomly distributed in Kuwait. This finding holds even when complaints are broken out by season, by type, or both.

Local-level pattern analysis

As mentioned in the data and methods section, the complaints were aggregated to the neighborhood level, and thus each neighborhood will have a complaints count. In their research, Lu and Johnson (2016) used total counts to perform the hotspot analysis. In this research, the total count was normalized by the total population to ensure that cluster detection is not biased toward high population neighborhoods. The count of complaints was divided by the total population of $neighborhood_i$, then multiplied by 1,000 to get the rate of complaints per 1,000 people. The population data used was from the 2011 census. After implementing the research question criteria in Figure 4.3, the total count of complaints was 3,543 out of 4,958 geocoded complaints representing 71.5%. When aggregated to the neighborhood level, the count of neighborhoods with at least one complaint was 112 out of 121, representing ~93% of all neighborhoods in the metropolitan area (Figure 4.18). The reason for the larger sample size in the local analysis relative to the preceding global analysis is once again that some complaints could be geocoded to a neighborhood – but not to a precise point location within that neighborhood (which would be needed for a complaint to be included in point pattern analysis).

Upon converting complaint counts into rates, several extreme values were observed. For instance, the Airport area had a complaint rate of 1,482 per 1,000 people. This anomaly is due to the low population count in this area (29 people), and the total complaints were 43 (Figure 19). To ensure that these extreme values would not bias the analysis, an outlier detection process was followed. Using the first and third quartiles and the interquartile range (IQR), values below -9.3 or above 17.1 were considered outliers and excluded from the analysis (Figure 4.19). The total number of neighborhoods after excluding the outliers was 97. It should be noted, however, that while the outlying neighborhoods shown in Figure 4.19 are omitted from statistical analysis because of their large influence; they should not be omitted from public discussion. Stated alternatively, the high number of complaints in these spaces relative to the number of residents seems to suggest that the areas require government attention and intervention.

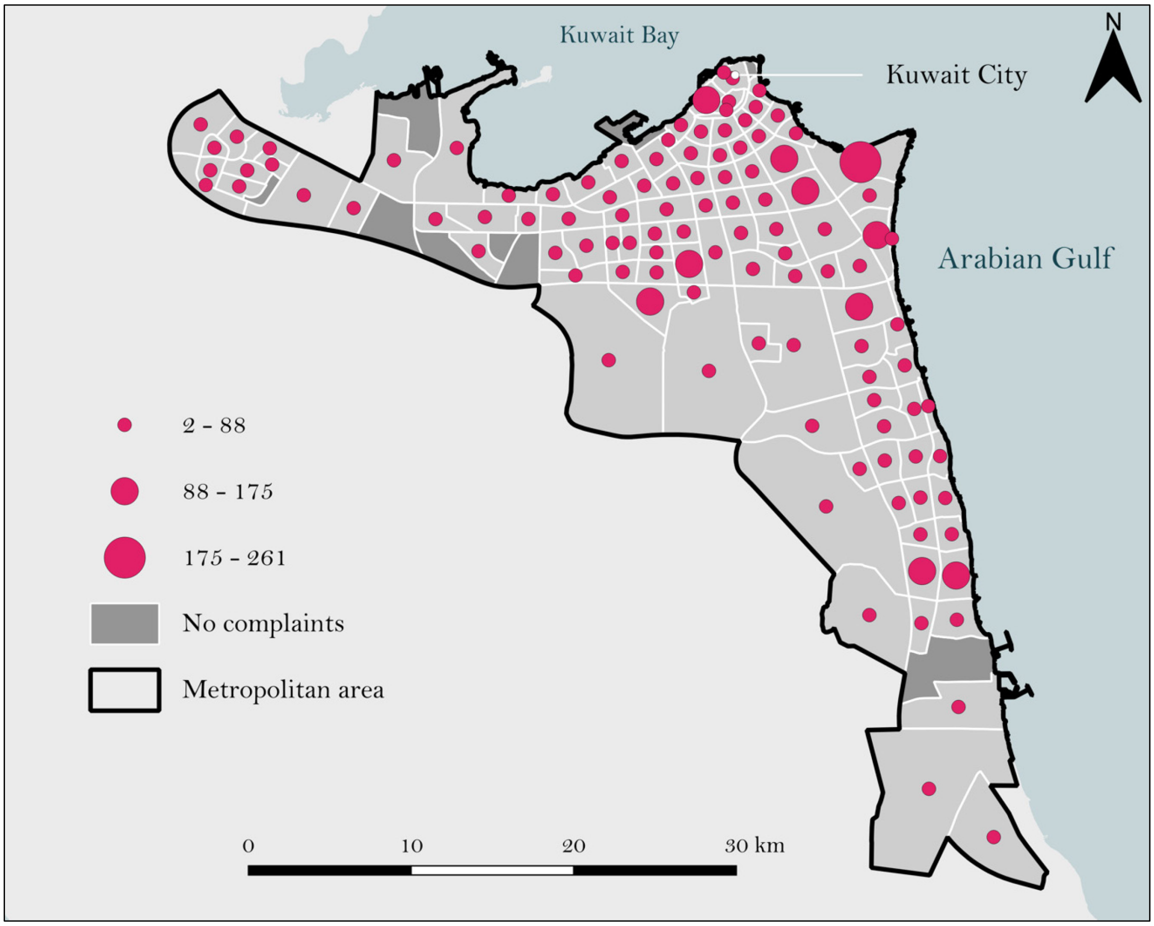


Figure 4.18. Count of complaints at each neighborhood. This map is the result of the aggregation process.

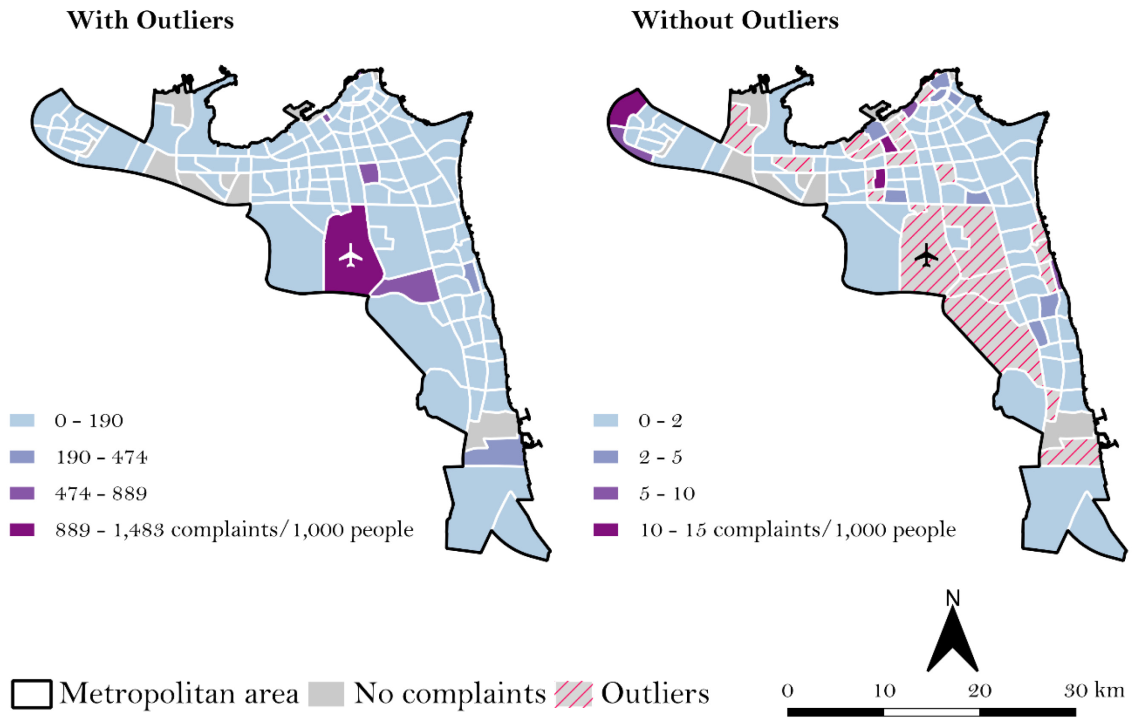


Figure 4.19. Normalized complaints and the detected neighborhood outliers.

The normalized complaints during each season are shown on the maps in Figure 4.20. The seasonal frequency of the aggregated complaints is shown in Figure 4.21. Fall had the largest count of complaints in 2019 at the neighborhood level, with 1,113 complaints (31.5%); while spring had the lowest frequency of complaints, with 767 complaints (27.7%).

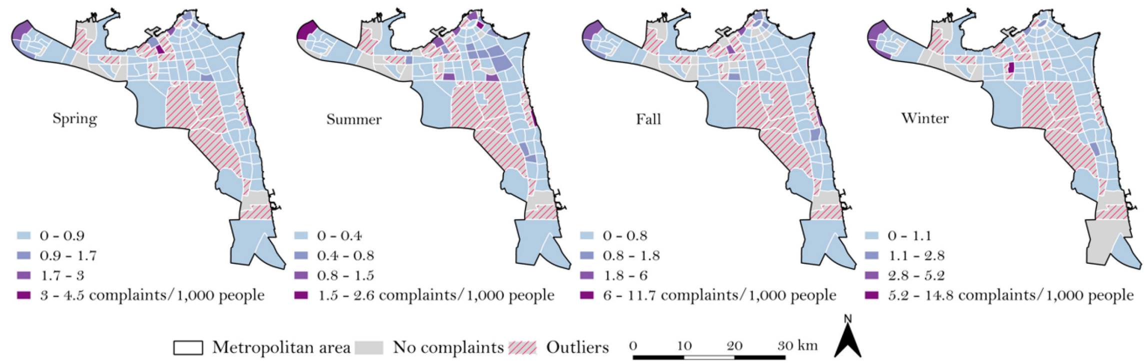


Figure 4.20. Seasonal maps of normalized complaints.

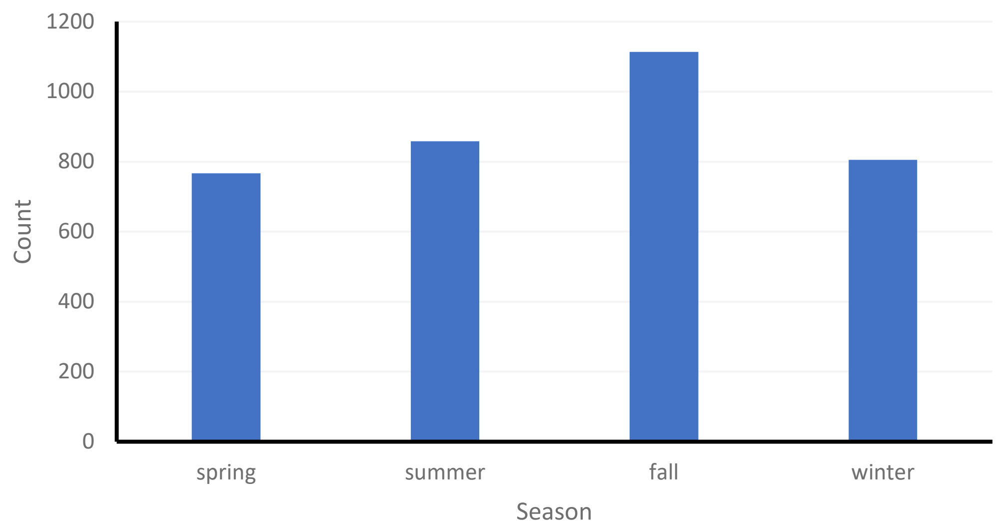


Figure 4.21. Seasonal count of complaints that are at the neighborhood level.

Similar to research question 2b, the top two complaint types were again mun and inf after aggregating complaints to the neighborhood level. Table 4.4 summarizes the frequency of the top complaint types for research question 4. The spatial distribution of the normalized complaints for both types is shown on the maps in Figure 4.22.

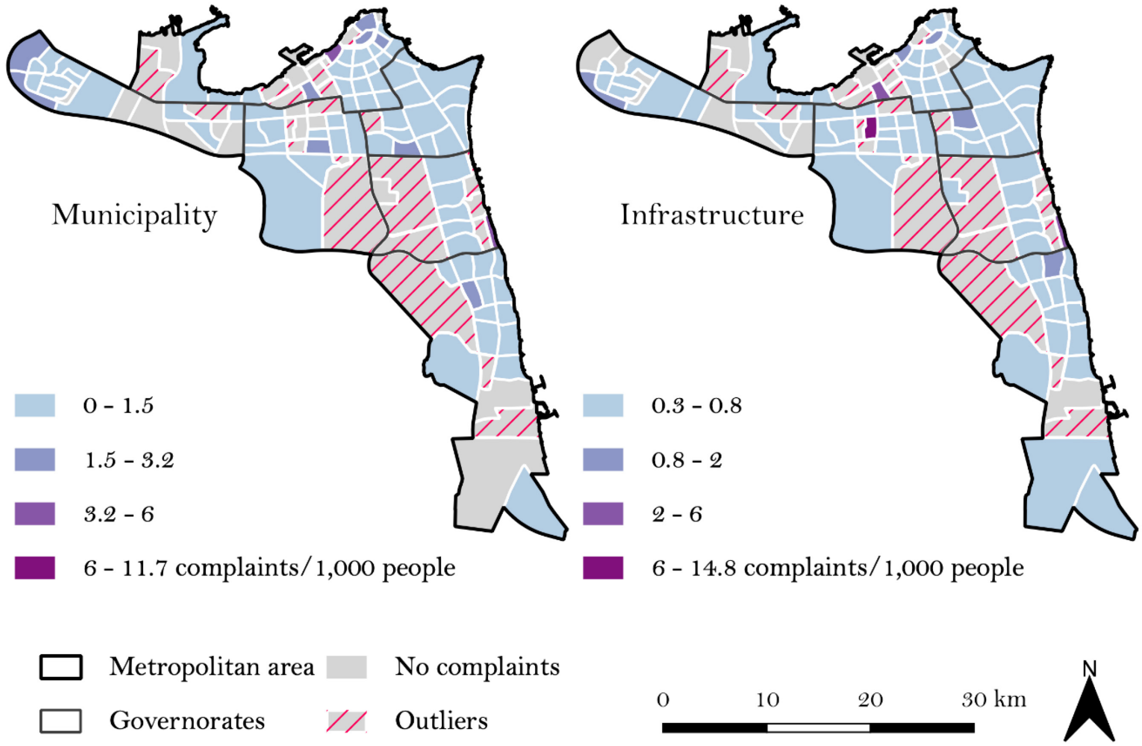


Figure 4.22. Normalized complaints of the top two types.

The seasonal frequencies for both types are presented in Figure 4.23, and the seasonal spatial distributions are shown on the maps in Figure 4.24.

Table 4.4. Research question 4 top types frequency.

Complaint type	Count	Percentage
Municipal	1,854	52.3
Infrastructure	887	25
Mixed	214	6.1
Utilities	190	5.4
Administrative	145	4.1
Landscape	137	3.9
Social	98	2.8
Environment	18	0.5

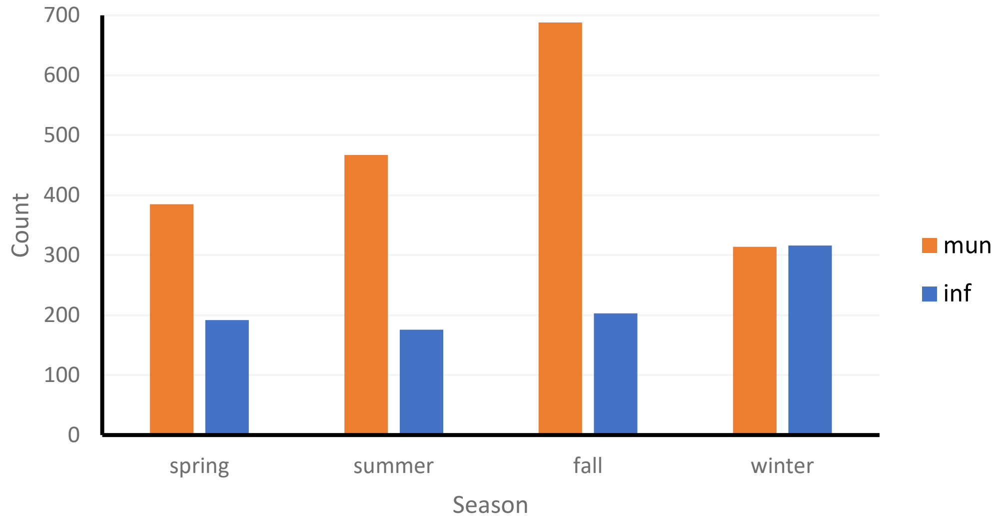


Figure 4.23. Research question 4b seasonal count of complaints.

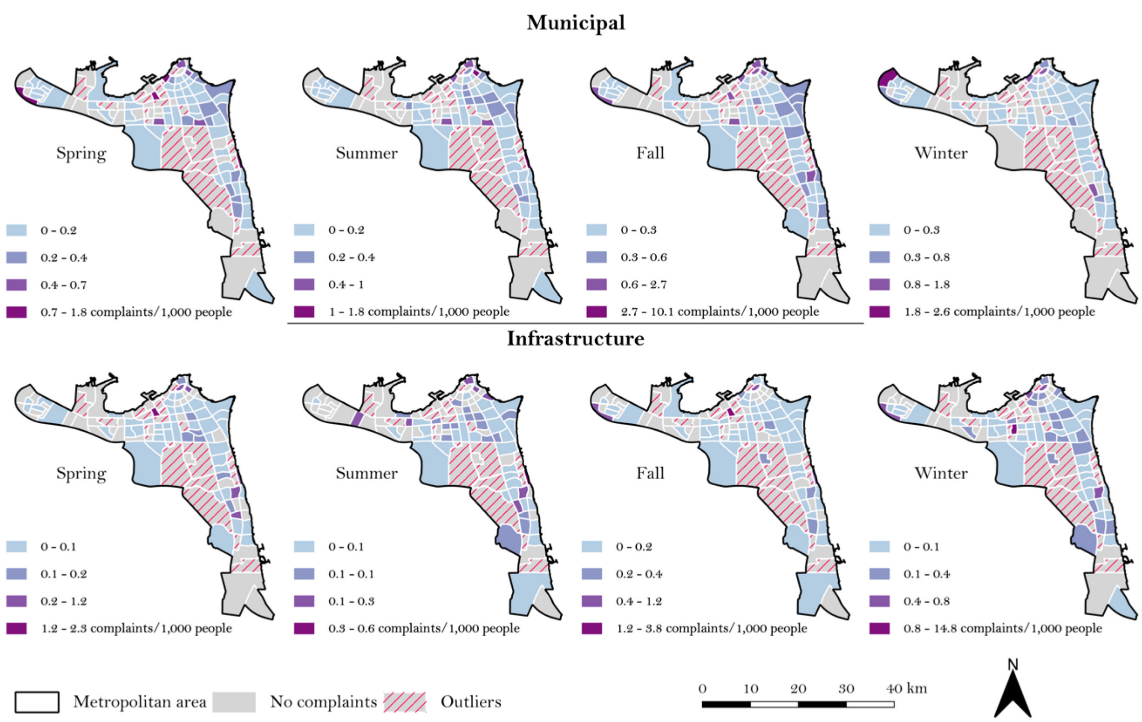


Figure 4.24. Research question 4b spatial distribution of normalized complaints during each season.

***Gi** results**

The results of the *Gi** analyses for research question 3a are shown in Figure 4.25. Visually, both high (hot spot) and low (cold spot) clusters were identified in the northern portion of the study area. There are adjacent low cluster neighborhoods west of Kuwait City. Most high clusters are relatively close to Kuwait City, except for two neighborhoods in the far west of the study area.

The results for research question 3b are shown in Figure 4.26. The seasonal analysis revealed several patterns that were not observable when *Gi** was performed for the whole year. Several high clusters were detected around the City during spring. In spring, there was one "hot spot" of complaints in the southern half of Kuwait that was not detected when complaints were aggregated for the full year. During summer, there was a limited existence of high clusters around the City. Then, several high clusters appeared in the eastern parts of the study area in fall, and, finally, the cluster shifted towards the central part of the study area and towards the west during winter. Regarding low clusters, the spatial pattern and extent were generally consistent during all seasons, where the low clusters are situated in the center of the study area and extend towards the western parts (similar to the finding of research question 3a). There was an exception during fall, where fewer neighborhoods were detected as low clusters in the central part.

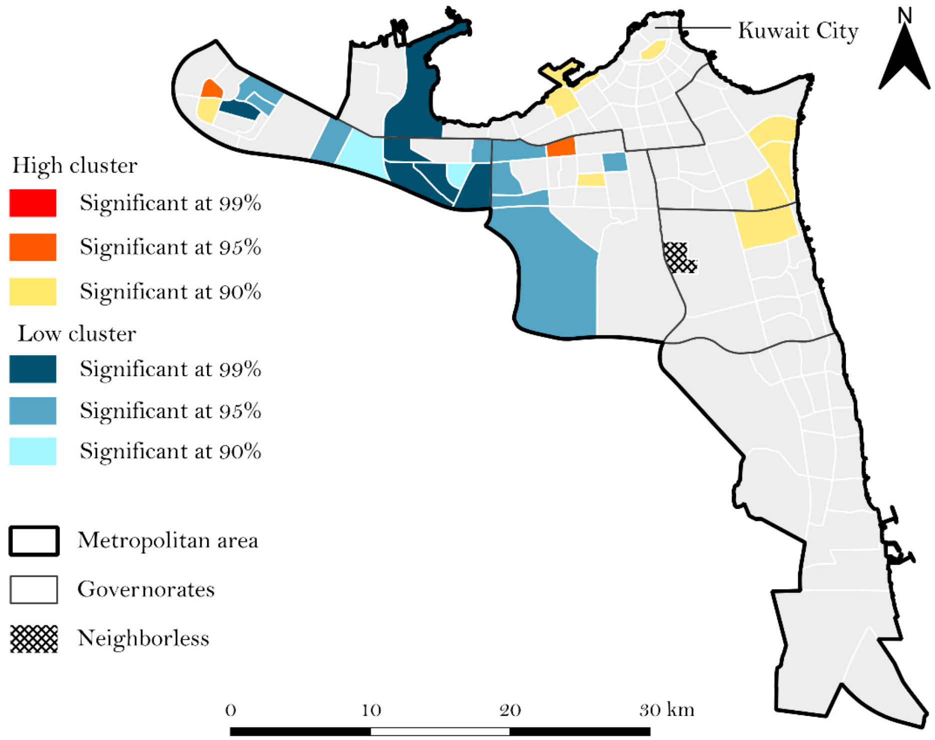


Figure 4.25. ***Gi**** **hotspot analysis results for research question 3a.**

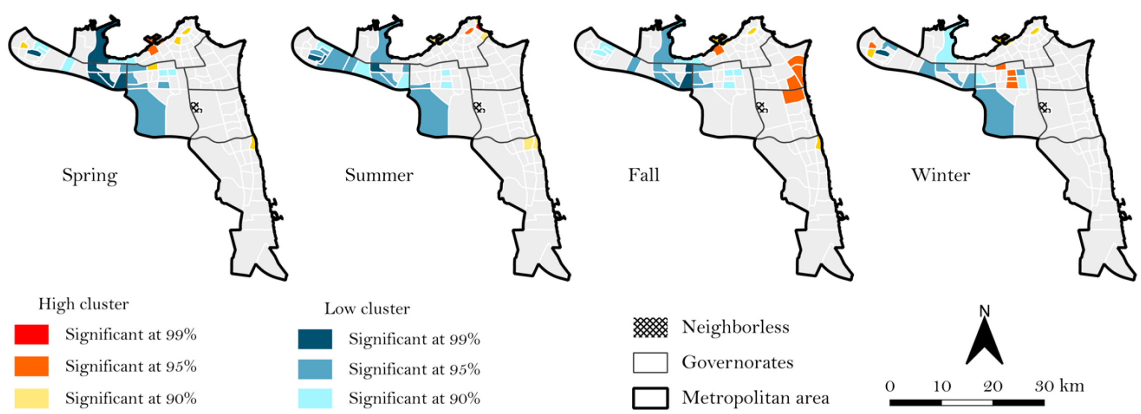


Figure 4.26. ***Gi**** **hotspot analysis results for research question 3b.**

The results of *Gi** hotspot analysis for research question 4a are illustrated in Figure 4.27. Hot spots of mun complaints were detected near Kuwait City, and several high spots emerged in the eastern part of the study area. On the other hand, low clusters showed a similar pattern to the findings of research question 3, where a contiguous low cluster takes shape west of the City. The southern region of the study area exhibited a high and low cluster of mun complaints. Regarding inf complaints, high clusters were identified in the center of the study area (west of the high clusters that were detected in mun results). The low cluster was similar to the defined pattern in mun complaints, where they mostly exist in the west region of the study area. Similarly, inf complaints exhibited a high cluster in the southern region. Also, there was a unique case of low cluster detected proximate to the City.

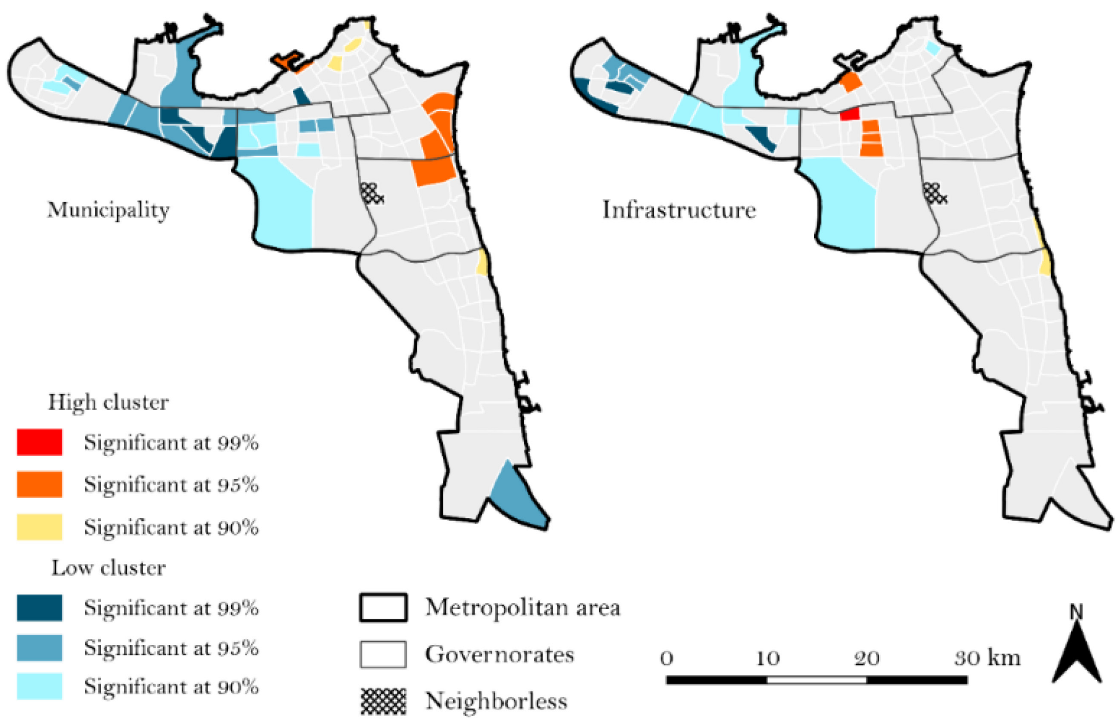


Figure 4.27. *Gi hotspot analysis results for research question 4a.**

The results of *Gi** analysis for research question 4b are illustrated in Figure 4.28. The results of the high cluster revealed varying patterns through the seasons for both types. During spring, multiple clusters emerged. High clusters were detected mostly in the eastern, central, and western parts of the study area. The pattern of the low clusters tended to be observable in the western region with limited cases in the center of the study area. Furtherly, the southern region exhibited high and low clusters. In the summer, mun high clusters were detected near the City and towards the southern region. The low clusters had a similar spatial distribution to the previous findings: they occur prominently in the western region and sparsely in the southern region. During fall, a contiguous high cluster appeared in the eastern part of the study area. In contrast, the low cluster pattern remained similar to the summer, where it was detected in the western and western/central regions. During fall, the southern area did not exhibit any significant clusters. In the winter season, there were fewer clusters detected overall, compared to the other seasons.

Regarding inf seasonal patterns, high clusters were dispersed in the study area during spring, and more low clusters were found in the west except for one case that was proximate to the City. The pattern in spring had less significant clusters compared to those for mun during the same season. In the summer, high clusters were detected near the City and around the center of the study area. There was also a case of a high cluster in the western region, which was not true for mun complaints. There were limited low clusters, compared to mun in the summer, but they were detected in similar parts of the study area (west and south regions). During fall, fewer high clusters were detected compared to summer, and they were located in the northern parts of the study area (with one in the southern region). Following a similar pattern to most previous findings, low clusters were found in the western and the southern areas. Finally, during winter, high clusters were identified in the center of the study area, and low clusters had a varying pattern where it was detected in the west, center, and south areas.

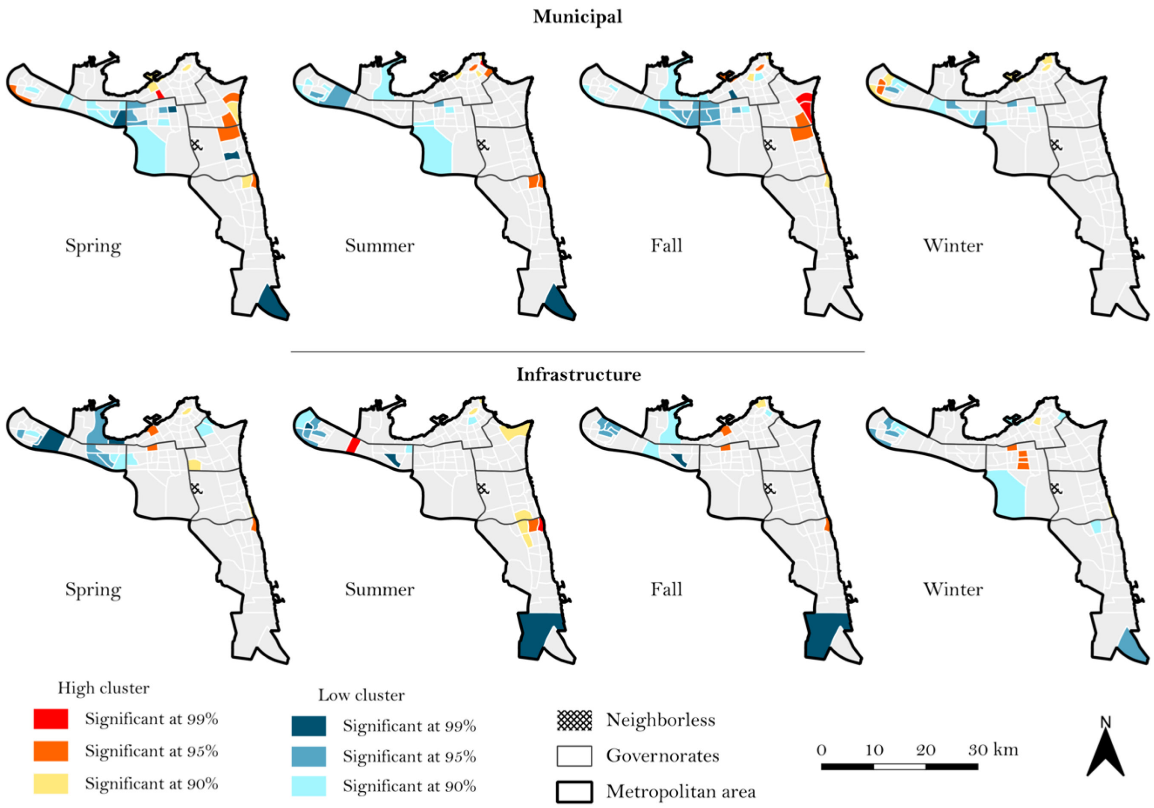


Figure 4.28. ***Gi**** **hotspot analysis results for research question 4a.**

Discussion

There have been few attempts at global point pattern analysis of citizen complaints in previous research, perhaps because global statistics provide only limited insights into the character of spatial patterns. That is, they can detect clustering, but they do not reveal where in the pattern values are clustered. Possibly for that reason, the literature that does evaluate spatial patterns of citizen complaints bypasses global analysis and employs local statistics to identify hot or cold spots of non-emergency requests (Lu and Johnson 2016). As one of the first attempts to study such patterns outside of a U.S.-centric context and using alternative sources of data, however, this chapter aimed to characterize spatial patterns of citizen complaints in Kuwait as fully as possible.

With that in mind, this chapter began with global point pattern analysis. Since citizen complaints are mostly concerned with the urban commons, it is assumed that they would be located in populated areas with public services that exhibit daily civic activities (e.g., transportation networks or residential buildings) or where such services are consumed. If true, then complaints should not exhibit a random distribution. This chapter tested the null hypothesis of spatial randomness via two methods that were applied to various breakouts of my point-level complaint data. Taken together, the findings allow for a rejection of the null hypothesis of spatial randomness.

Detecting clustering in the complaint data is consistent with prior research on U.S.-based 311 systems. That being said, recognizing that complaint patterns are clustered is of negligible value without identifying where clustered values (whether high or low) occur. Such questions are the domain of local statistics. While the local cluster detection analyses performed above began from an agnostic perspective that did not formulate hypotheses about where or why local clusters might occur (these questions are taken up in the next chapter), for interpretative purposes it might be helpful to first explore the complaint distribution before discussing the Gi* results.

In Figure 4.29 remaps the point distribution of complaints from above, but using cartographic techniques (specifically, kernel density heat mapping [A] and hexagonal binning [B]) to highlight locations where complaints occur with greater intensity. Both maps from Figure 4.29 depict an outcome that is empirically supported in most of the local cluster analyses (see below). Namely, greater concentrations of complaints occur near Kuwait City in the north and east, with relatively few complaints in the western part of the study area. These patterns aid my interpretation of the Gi* results in the next subsection.

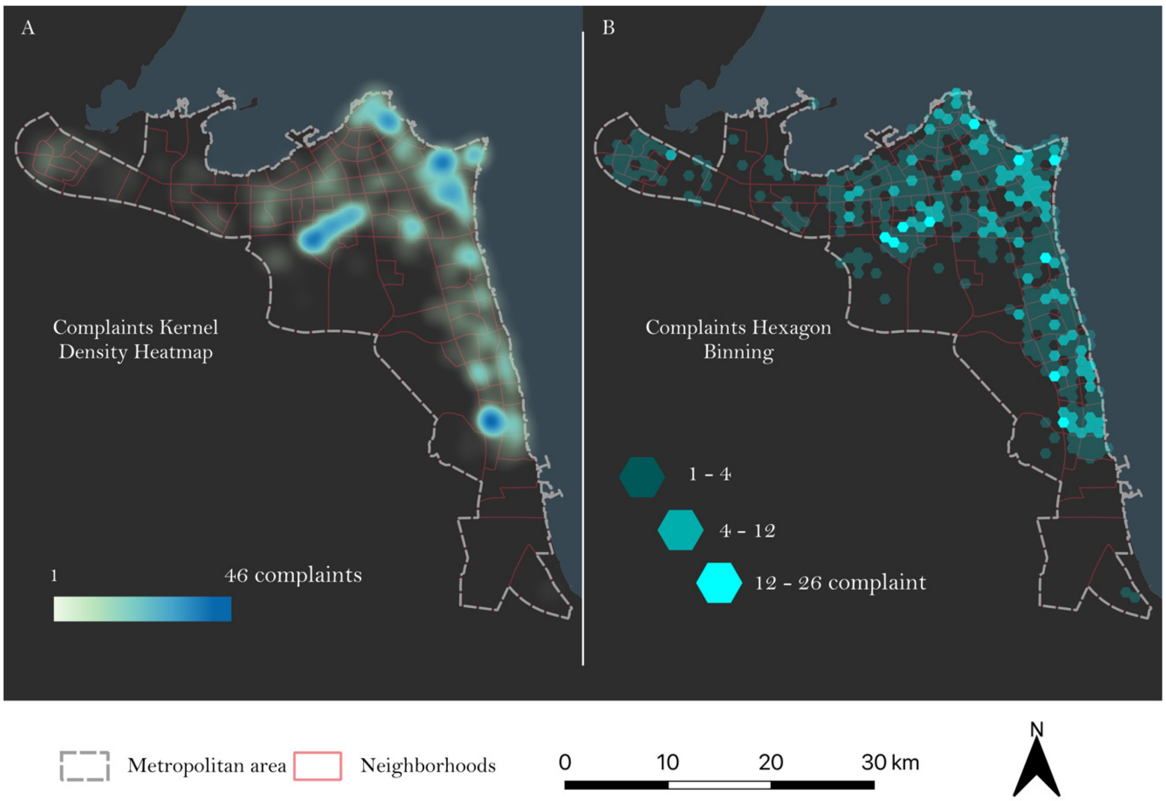


Figure 4.29. Exploratory Spatial Data Analysis (ESDA) of complaints. (A) a kernel density heatmap, and (B) hexagon bins for complaints.

Local-level discussion

Once a clustered pattern is identified via global statistics, the next step is often to identify the precise locations of high (hot) or low (cold) clusters at the neighborhood level. Research questions 3 and 4 sought precisely such information. Both high and low clusters were identified in the complaint data; however, the precise locations and patterns of clusters varied by both season and type.

Recall from Figure 4.25 that high complaint clusters were detected Kuwait City and in the eastern section of the study area, while low clusters were mostly found in the western part of the study area. Comparing this overall pattern with the seasonal pattern in Figure 4.26, high clusters exhibited notable seasonality, while low clusters remained mostly constant and were concentrated in the west.

Recall from both Chapter 1 and Chapter 2 that one predictor of citizen complaints to governmental agencies, which are grounded in citizen dissatisfaction with the government's management or provision of public goods and services, is population pressure. More specifically, urbanization and urban growth make it more difficult for governments to provide high quality governmental goods to all residents in all places. On that backdrop, the existing literature implies that complaints – even when normalized by population – might be skewed toward urban and urbanizing spaces (e.g., Lu and Johnson 2016).

Consistent with these observations, the local clusters detected in this chapter show inchoate evidence that complaints are more common in urbanized areas near Kuwait City and less common in less densely populated neighborhoods. To be sure, Figure 4.30 maps residential density across Kuwait. The map shows that the western region of the study area is mostly characterized by low to medium residential density, while areas near the City (in the north) and along the eastern boundary to the south are characterized by higher residential density. This pattern exhibits striking similarities with distribution of complaints visualized in Figure 4.29.

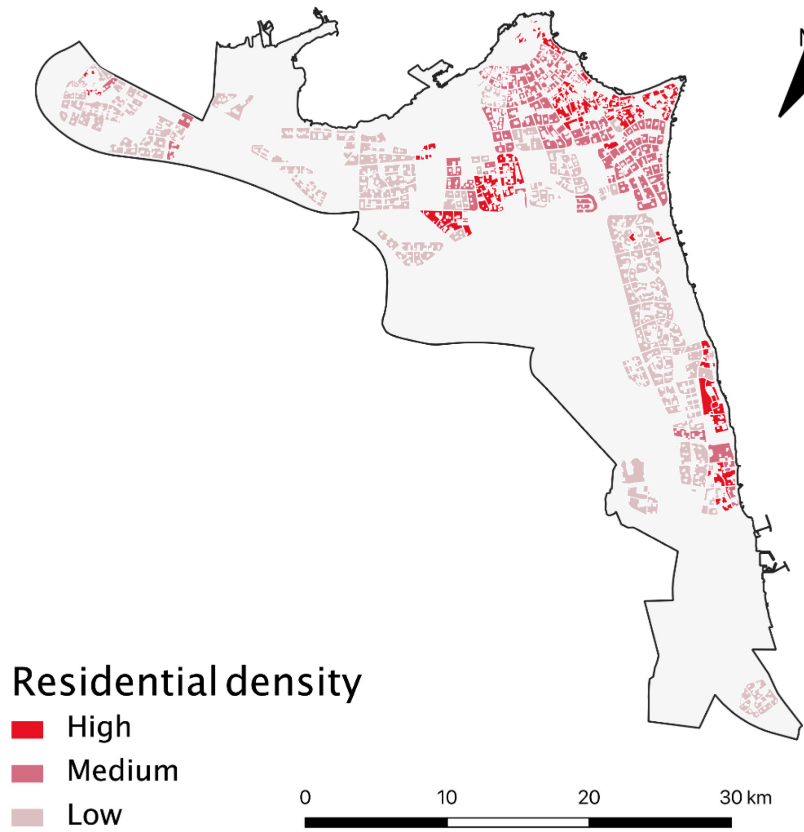


Figure 4.30. Residential density from the 2010 land use map. Data after (Environmental Public Authority 2020).

Another reason for the spatiotemporal variation of clusters could be due to the continuous population mobility in and out of Kuwait during specific seasons. Obtaining socioeconomic records for the population at a high temporal scale is not possible in Kuwait. An alternative could be the estimated traveling reports from the Central Statistical Bureau (2020). Between June and September 2018, it was estimated that ~2.3 million people departed the country (Figure 4.31). It is plausible that seasonal variations in population flows contribute to changing spatial patterns for all or specific types of complaints.

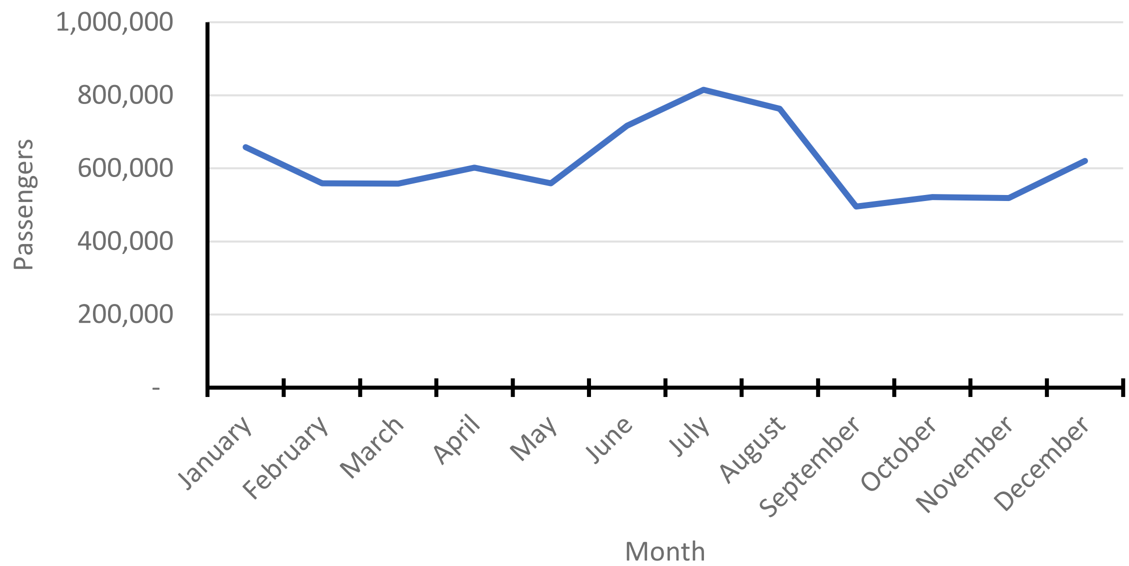


Figure 4.31. Kuwait airport departures statistics in 2018.

The possibilities raised above, and countless others, suggest that point pattern analysis and cluster detection offer only limited insights into the spatial distribution of citizen complaints. Whereas such analyses are useful for characterizing distributions and, potentially, targeting resources and government interventions (i.e., directing resources to hot spots in the appropriate season(s)), they do not reveal any information about the processes that produce those patterns. In that sense, even if governments become more efficient at responding to complaints in identifiable hot spots, the implication is that the hot spots will continue to emerge. Consequently, a critical next step is to attempt to explain variability in complaint patterns, to better understand why hot spots form where they form. This task is taken up in the next chapter, which creates and estimates multiple regression models to explain variation in neighborhood-level complaint rates as a function of available demographic and socioeconomic indicators.

In extension to the research's theoretical background, the results reflect the motivation to share complaints through the sense of owning the place (i.e., territoriality) and co-production. Such motivations were not spatially random and exhibited varying spatiotemporal clusters at the local-level. This indicates that territoriality and co-production in Kuwait are a function of certain socioeconomic factors that vary in magnitude from one area to another. The next chapter examined these factors and how they derive unbalanced territoriality and co-production from a spatial perspective.

Conclusions

Exploring spatial patterns of non-emergency requests is the first step towards understanding the processes or factors that derived these patterns. In this chapter, the spatial pattern of citizen complaints in the metropolitan area of Kuwait was examined at global and local levels. At the global level, the complaints were clustered at all times and during each season. The same pattern held for the two most frequent complaint types during all and each season.

At the local level, results showed that low clusters of complaints were mostly located in the western parts of the metropolitan area during all times. High clusters, on the other hand, showed more dynamic patterns during seasons and for both types. At the coarser temporal resolution (whole year), the government could re-allocate their resources to resolve requests at high clustered areas and reduce the concentration on low clustered areas. At a higher temporal resolution (seasonal), high clusters exhibited spatial shifting. It would more complex to keep re-allocating human resources based on seasonal patterns. A more cost-effective measure would involve trying to explain seasonal variation as a function of relevant contextual data at that higher temporal (seasonal) resolution. Future research in that direction could arguably allow governments to better grasp the processes that generate complaint patterns, anticipate certain issues, and proactively address those issues before they ever lead to citizen complaints.

Until the data to inform such studies become available (possible), the findings from this chapter point to at least six actions that could be taken in the near term to enhance governmental service monitoring and response:

1. Re-allocate human resources to be consistent with the location of high clusters, but also consider any inequality in reporting complaints (will be discussed in Chapter 5)
2. Integrate authoritative records of requests with social media data to leverage the analysis of citizen complaints.
3. Use authoritative records of requests in a comparative analysis against social media data to identify any differences or similarities from a spatiotemporal perspective.
4. Expand the temporal analysis for robust seasonal spatial patterns by adding previous year's complaints.
5. Acknowledge that social media represents an affective and secondary source of citizen complaints.
6. Develop customized location-based apps to collect, store, and redistribute citizen complaints to enable more population to request services and to enhance the locational scale of the requests.

5. SOCIOECONOMIC AND DEMOGRAPHIC CHARACTERISTICS AS PREDICTORS OF CITIZEN COMPLAINTS PROPENSITY AND GOVERNMENTAL RESPONSIVENESS

Chapter 4 examined spatial patterns of citizen complaints, revealing significant clustering in complaint volumes, with high concentrations of complaints in higher density neighborhoods (even after converting complaints into rates that account for underlying variation in population levels). As I observed in the final sections of the preceding chapter, attempting to explain variability in these nonrandom patterns using relevant socioeconomic and demographic covariates can begin to shed light on why clusters occur in some spaces, and which groups of citizens are more likely to make complaints. Prior research on 311 and equivalent systems point to several socioeconomic characteristics that vary systematically with non-emergency complaints made by citizens to their local governments, including age, income, race/ethnicity, and education (e.g., Cavallo, Lynch, and Scull 2014; Lu and Johnson 2016; Minkoff 2016).

In a more general sense, existing scholarship tends to find a link between complaint volumes and what researchers call indicators of a *digital divide*. The digital divide refers to inequitable levels of access to information and communication technologies (ICTs) and gaps in knowledge and technical skills with respect to those technologies (Kuk 2003). Document such a divide is often done using empirical indicators of socioeconomic status. For instance, (Goldfarb and Prince 2008) found that internet usage is positively correlated with both income and educational attainment, suggesting that disparities in these latter variables contribute the production of a digital divide. Likewise, gender, race, and citizenship have all been found to correlate with online participation among individuals, with the consistent result that more marginalized demographic groups tend to have poorer access to ICTs, thereby contributing to the creation of a digital divide (Crutcher and Zook 2009; Stephens 2013).

Taking cues from this established research, the current chapter investigates variability in complaint volumes in Kuwait at the neighborhood level, as a function of multiple socioeconomic factors that are relevant to the concept of a digital divide (Cavallo, Lynch, and Scull 2014; Lu and Johnson 2016; Minkoff 2016). The analysis is carried out using a combination of *Factor Analysis* (*FA*) and *Multiple Regression* (*MR*).

Building on that foundational research, however – in addition to extending it to consider a volunteer-run social media (SM) system outside of the U.S. – this chapter analyzes not only variability in complaint patterns; but also variation in governmental responsiveness to complaints. Responsiveness is studied both in terms of frequency (i.e., the volume of complaints that are resolved) and time. Concerning the latter, responsiveness time is defined herein as the time difference between when a complaint was requested/posted and when the same complaint was fixed/resolved. Much like complaint volumes, patterns of responsiveness may exhibit systematic variation with neighborhood-level socioeconomic characteristics (e.g., higher responsiveness in more affluent areas). Investigating these patterns and possibilities is critical to understanding the extent to which governmental goods (Ch. 2) are provided equitably throughout Kuwait.

On that backdrop, the precise research questions toward which the analyses in this chapter are directed are:

1. Are there systematic relationships between neighborhood-level complaint volumes and socioeconomic and demographic factors in Kuwait?
2. Are there systematic relationships between government responses to neighborhood-level complaints and socioeconomic and demographic factors in Kuwait?
3. Are there systematic relationships between government response time to neighborhood-level complaints and socioeconomic and demographic factors in Kuwait?

Embedded in each of these three questions are multiple interrelated null hypotheses of the following form:

$$H_0: \beta_{i,j} = 0,$$

where β is a regression parameter summarizing the partial relationship between socioeconomic or demographic factor i and the dependent variable in the j^{th} regression model. The dependent variables under consideration in research questions 1-3 are, respectively, neighborhood level complaint volume, fraction of neighborhood complaints resolved by the government, and government response time.

To set up tests of these hypotheses, the next section begins by identifying socioeconomic variables that feature frequently in the literature and describing ways in which variables similar to those U.S.-centric variables can be measured in Kuwait. Next, the chapter describes the structure and design of the data used to answer the preceding research questions. That discussion is grounded in the main Entity Relationship Diagram (ERD) from Chapter 3 (Figure 3.10). From there, the chapter describes and justifies the choice of methods, followed by a presentation of the results. Finally, the chapter concludes with a discussion and interpretation of the results.

Data and methods

As mentioned above and covered more deeply in the literature review conducted in Chapter 2, 311 researchers have identified several common independent variables that appear to explain variability in patterns of citizen complaints. The most common of these variables are summarized in Table 1 alongside accompanying references. Race and education variables are used most often in the literature. Employment, crime rates, and total population are among the indicators that appear somewhat less frequently in existing studies.

For Kuwait, available census data contains several variables the correspond closely to the measures described in Table 5.1. For example:

- Total population is available in the Kuwait census. However, because larger populations are arguably more predisposed to generate more complaints, population is incorporated into the following analyses using population density rather than raw population counts (for normalization purposes)
- Language is not part of Kuwait's census, and therefore cannot be incorporated directly into the models that follow.
- As discussed in chapter 3, the Kuwait census does not collect data on income. As a proxy, average residential real estate prices at the neighborhood level are used to indicate neighborhood affluence. This approach is similar to Wang and colleagues' (2017) use of housing prices to study citizen complaints.

- Arguably the most common demographic in western literature is race/ethnicity. However, in Kuwait, administrative agencies do not collect such data. Instead, the Kuwait census tracts the nationality of respondents. Thus, in place or race/ethnicity, subsequent analyses substitute nationality.
- Finally, neighborhood-level crime data are not available from existing data sources in Kuwait and therefore cannot be integrated into the statistical models.

Apart from these minor inconsistencies, the remaining variables common to the U.S.-centric literature (Table 5.1) – including age, gender, citizenship status, education, household size and composition, marital status, and employment status – are all represented in Kuwait's census data. Beyond these common variables, and returning to the notion of a digital divide, Kuwait's census includes data on internet and computer usage at the neighborhood level. Because of their relevance for reporting complaints to an online SM account, these variables were deemed essential to the goal of explaining variability in complaint patterns.

Table 5.2 summarizes the variables used in this Chapter by theme.

Table 5.1. Common socioeconomic variables used in 311-related research.

Socioeconomic variable / **Reference**	(Wang et al. 2017)	(Minkoff 2016)	(O'Brien 2016)	(Cavallo, Lynch, and Scull 2014)	(Kontokosta, Hong, and Korsberg 2017)	(Lu and Johnson 2016)
Total population						Y
Age			Y	Y	Y	Y
Gender			Y	Y	Y	Y
Citizenship				Y		Y
Language					Y	Y
Income	Y	Y				Y
Educational level/degree	Y		Y	Y	Y	Y
Household variables		Y		Y	Y	
Race	Y	Y	Y	Y	Y	
Marital status					Y	
Employment	Y	Y			Y	
Crime		Y				

Table 5.2. Selected socioeconomic themes and variables in Kuwait.

Socioeconomic theme/variable	Notes
Population density	
Age	Available (age groups >=19 will be used to be consistent with the literature).
Gender	
Citizenship	Kuwaiti vs non-Kuwaiti
Real estate prices	A proxy for income level
Educational level/degree	
Household variables	There are multiple variables including: • Family member count • Average family size
Nationality	Used in place of more common race/ethnicity variables that feature in the 311literature
Marital status	
Employment	Employees by nationality and gender (for both Kuwaiti and non-Kuwaiti) is available
Technological variables*	There are multiple variables including: • Computer usage • Internet usage

* These variables are mostly overlooked in the 311-based literature, marking a contribution of this study.

Having situated variable selection for this chapter in existing 311 research, the next step is to develop the data. From the main ERD in chapter 3 (Figure 3.10), several tables with specific fields allow for the types of analyses needed to evaluate the three research questions posed above. Those tables are “complaints_t,” “response_t,” “neighborhoods,” “real_estate,” and “census_t.” The complaints included in the study are the same complaints used for research questions 3 and 4 from chapter 4, which examined spatial patterns at the neighborhood scale. Next, the “response_t” table contains all complaints that were responded to or resolved by government agencies. This table was used to identify the location of the resolved complaints and to calculate the time difference (“response time”) in days. The “census_t” table was used to select the variables enumerated in Table 5.2, along with the real estate averaged prices in the “real_estate” table. The “neighborhoods” table was then joined with the “complaints_t,” “census_t,” and the “real_estate” tables to facilitate the final analysis and visualization. The resulting ERD is shown Figure 5.1.

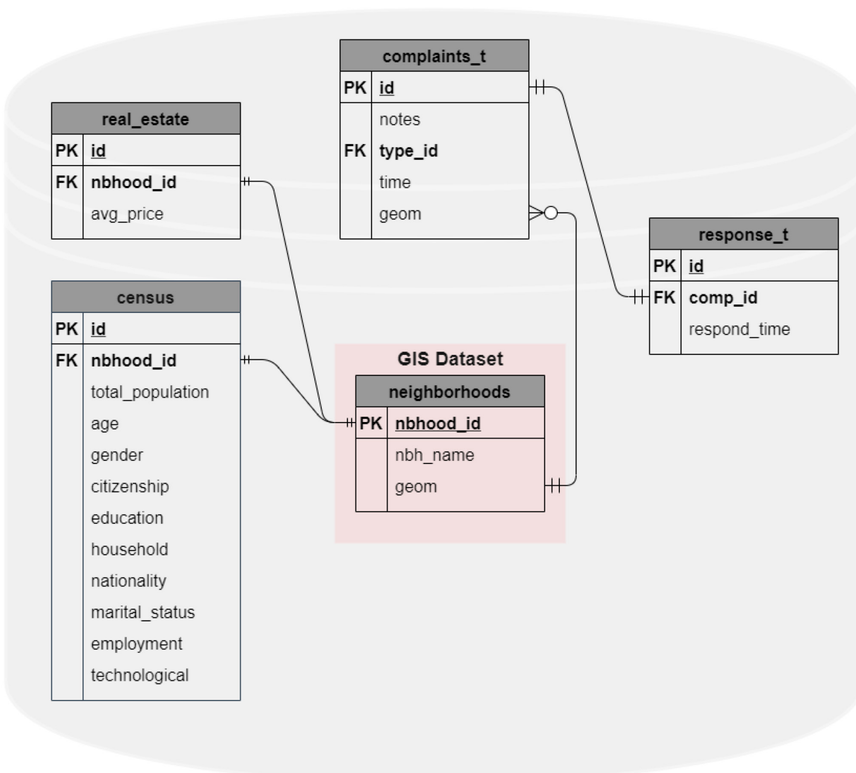


Figure 5.1. Overall ERD used for chapter 5 research questions.

The “complaints_t” table was joined with the “response_t” table on comp_id in a 1:1 relationship. Through this process, it was possible to have the original complaint time with the fixed time to calculate the responsiveness time in days (respond_time – time).

The geometry (geom field) of the responded complaints was joined from the “complaints_t” table, given that the resolved complaint has the same location. The resulting table (resolved complaints with the time difference) was then aggregated to the neighborhood level using the geom field from the “neighborhoods” and the complaints tables. Both census and real estate tables were joined with the neighborhood table on the nbhood_id field via a 1:1 relationship. The final table can ultimately be used to obtain the count of complaints (resolved and non-resolved) for neighborhood_i and thus perform the regression-based analyses.

In total, there were 44 socioeconomic variables that fell into the thematic categories listed in Table 5.2. As this chapter is, to my knowledge, the first attempt to study variability in patterns of citizen complaints in Kuwait, I submit that it is important to remain somewhat agnostic with respect to what variables “matter” and the direction in which they matter. While there are consistent findings along these lines in the western 311 literature (refer to Chapter 2), my study takes place outside of the global North and derives its data from a volunteer-run SM account rather than a formal government-sponsored complaint system. As such, it may not be advisable to pare down the list of candidate independent variables based solely on what levels of those variables have been significant in prior research. Consequently, in an effort to retain information from all potentially relevant variables in regression models, factor analysis (*FA*) was used to reduce the dimensionality of the independent variable dataset. The factors retained in FA can then be incorporated into the chapter’s multiple regression (MR) models. Using factors in these models instead of an unwieldy set of 44 independent variables is both a guard against multicollinearity and an efficiency measure.

Figure 5.2 summarizes the overall analysis flow of this chapter. From the database of this chapter, the main table was created to contain all the socioeconomic variables with the count of complaints, count of responded complaints, and the responsiveness time at the neighborhood level (the count of complaints was selected from chapter 4 research question 3 table). The first step was to perform the *FA* to identify the number of factors to be extracted and to compute factor scores for each extracted factor. The factor scores were then used as independent variables in the three *MR* models that correspond to the three research questions of this chapter (see above).

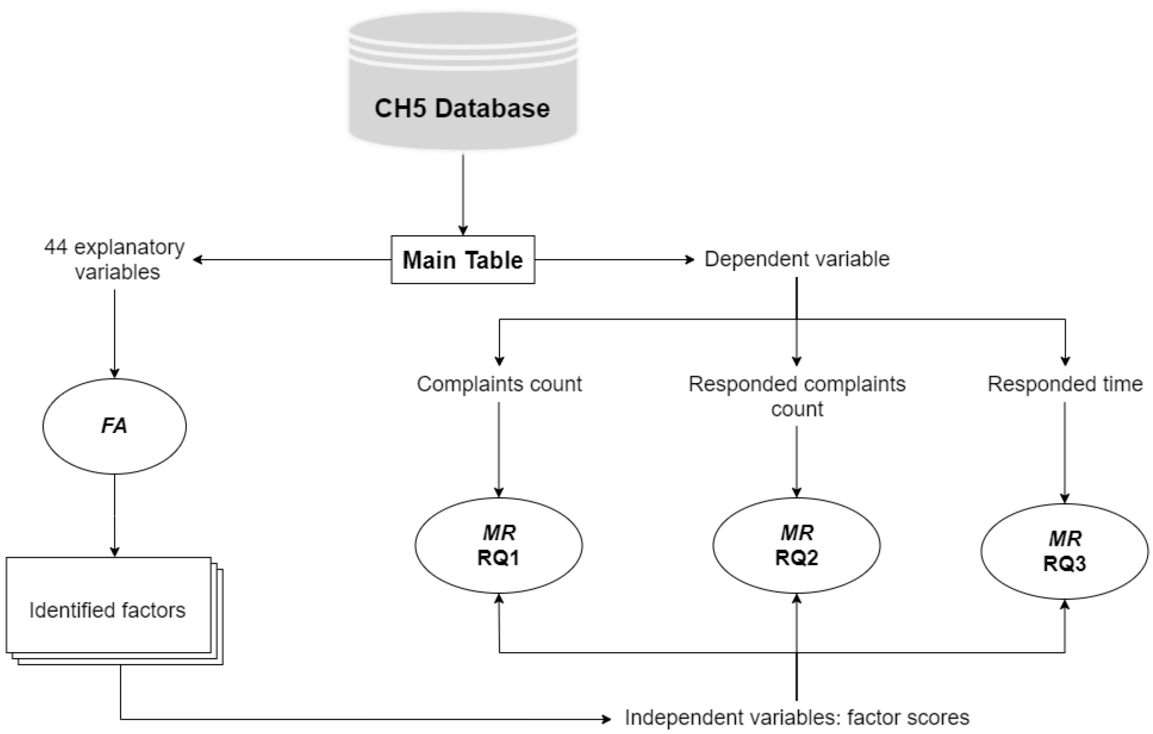


Figure 5.2. Chapter 5 research analysis chart.

Census data were available for all the 121 neighborhoods within the metropolitan area. However, real estate prices (my proxy for income or affluence) were not available for all 121 neighborhoods. As discussed in Chapter 3, real estate prices are mainly categorized into private housing, investment, commercial, and industrial lands. Private housing lands are areas where individuals can buy lands or houses for residential purposes. The other categories are invested by business groups, private institutes, or companies. Therefore, private housing prices are more suitable indicators of household income or affluence. For these reasons, the analyses were limited to the predominantly residential neighborhoods in Kuwait for which all socioeconomic and demographic data were available. The count of such neighborhoods was 69 out of 121 (Figure 5.3). With that in mind, the analyses described in Figure 5.2 were performed for the 69 neighborhoods pictured in Figure 5.3.

Because of the resulting disjointedness in the sample of neighborhoods retained in the analyses – in other words, by excluding nonresidential spaces, some residential neighborhoods lose their spatial “neighbors” – conventional multiple regression (MR) was used rather than spatial regression (SR). The choice of MR over SR is well established in the 311 literature (e.g., Minkoff 2016). While SR would be preferred if all neighborhoods could be retained in the model (given the clustering observed in Chapter 4), using MR on a disjointed subset of neighborhoods is inadvisable since the models would necessarily misspecify the spatial relationships among neighborhoods (by excluding adjacent nonresidential areas). Identifying opportunities to overcome these challenges is a critical task of future research. With that being said, *FA* was carried out in R using the *psych* package (Revelle 2020). *MR* was conducted using JMP statistical software.

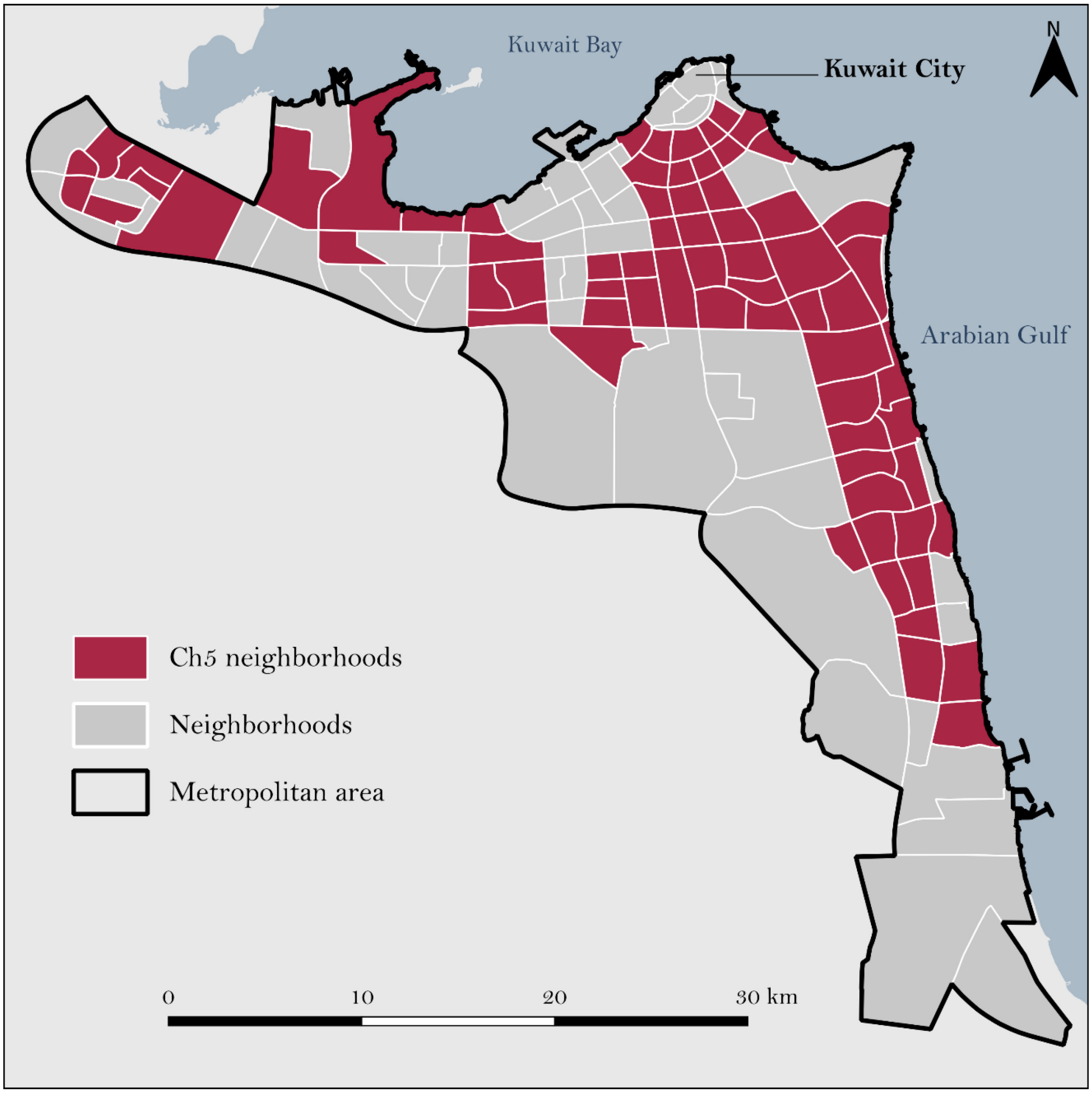


Figure 5.3. Chapter 5 neighborhoods included in the analysis.

Results

As mentioned in chapter 4, the total count of complaints aggregated to the neighborhood level was 3,543 out of 4,958 geocoded complaints (71.5%). The 69 predominantly residential neighborhoods identified in Figure 5.3 contain 2,318 of these 3,543 complaints (65.5%). The count of complaints for each of the 69 neighborhoods is shown on the map in Figure 5.4. Complaints are relatively high in a handful of neighborhoods near Kuwait City and along the eastern border of the study area. The western region in general is characterized by relatively few complaints.

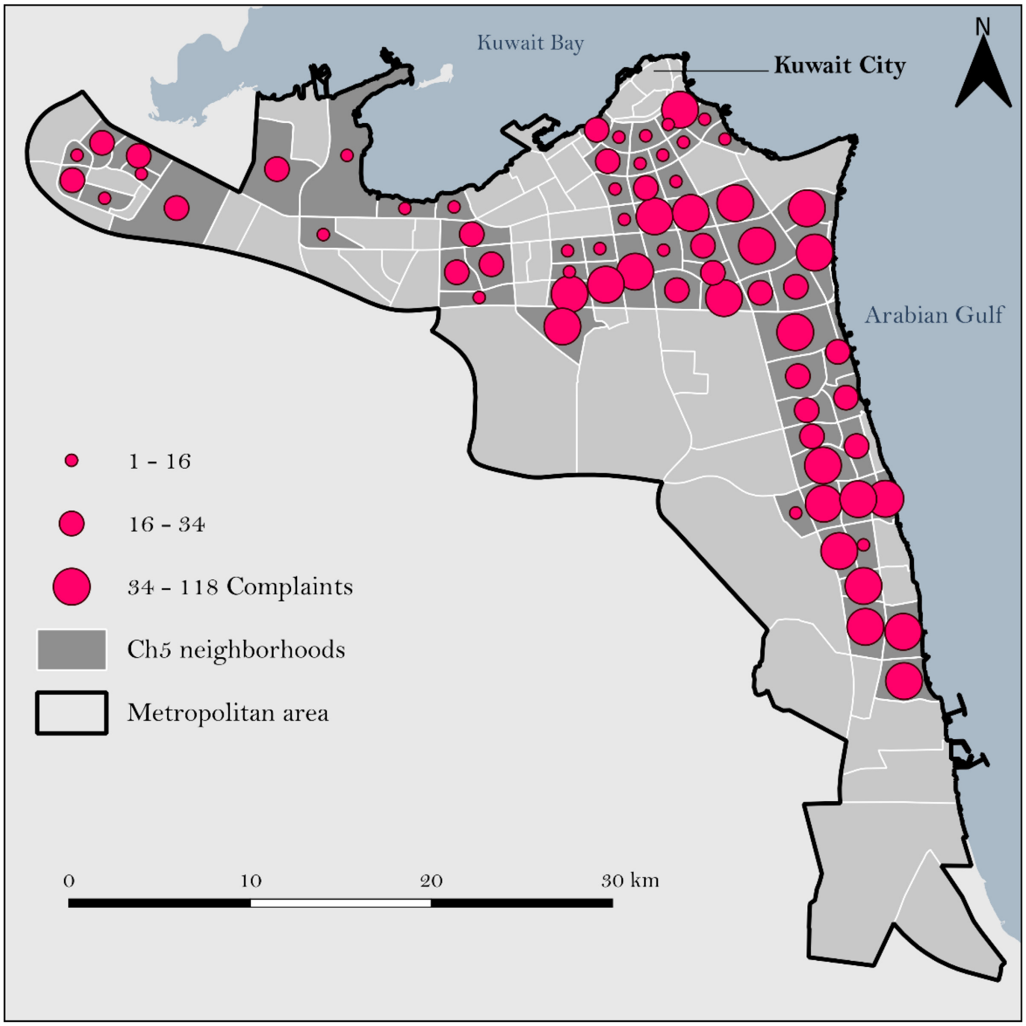


Figure 5.4. Count of complaints in chapter 5 neighborhoods.

Descriptively, among the full set of geocoded complaints, only 270 were identifiably resolved (7.6%). These resolved complaints were mostly, and intuitively, within the metropolitan residential area (Figure 5.5A). After narrowing these results to the 69 predominantly residential neighborhoods under investigation in this chapter, I found that 131 complaints were resolved across 44 of the 69 neighborhoods (Figure 5B). The aggregated count of resolved complaints for each neighborhood is shown in Figure 5.6. The central region in Figure 5.6 appears to have experienced greater responsiveness compared to other parts of the study area. However, because "eyeball estimates" are not reliable, additional analysis is needed (hence the MR models presented below).

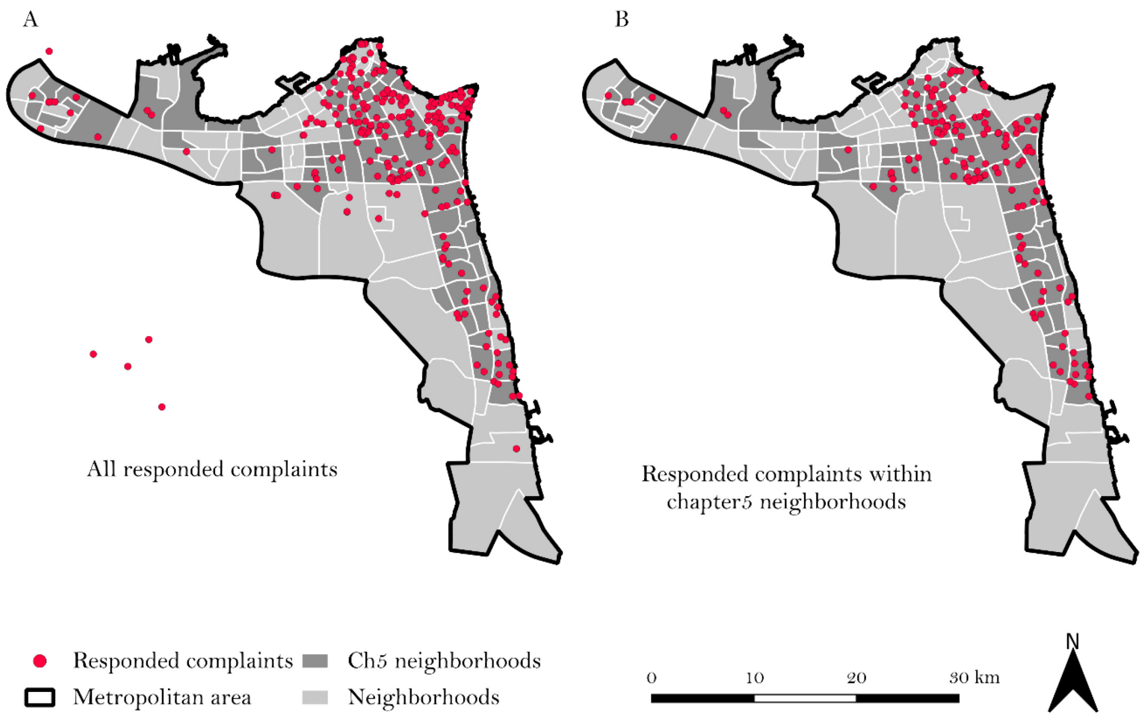


Figure 5.5. Spatial distribution of responded complaints.

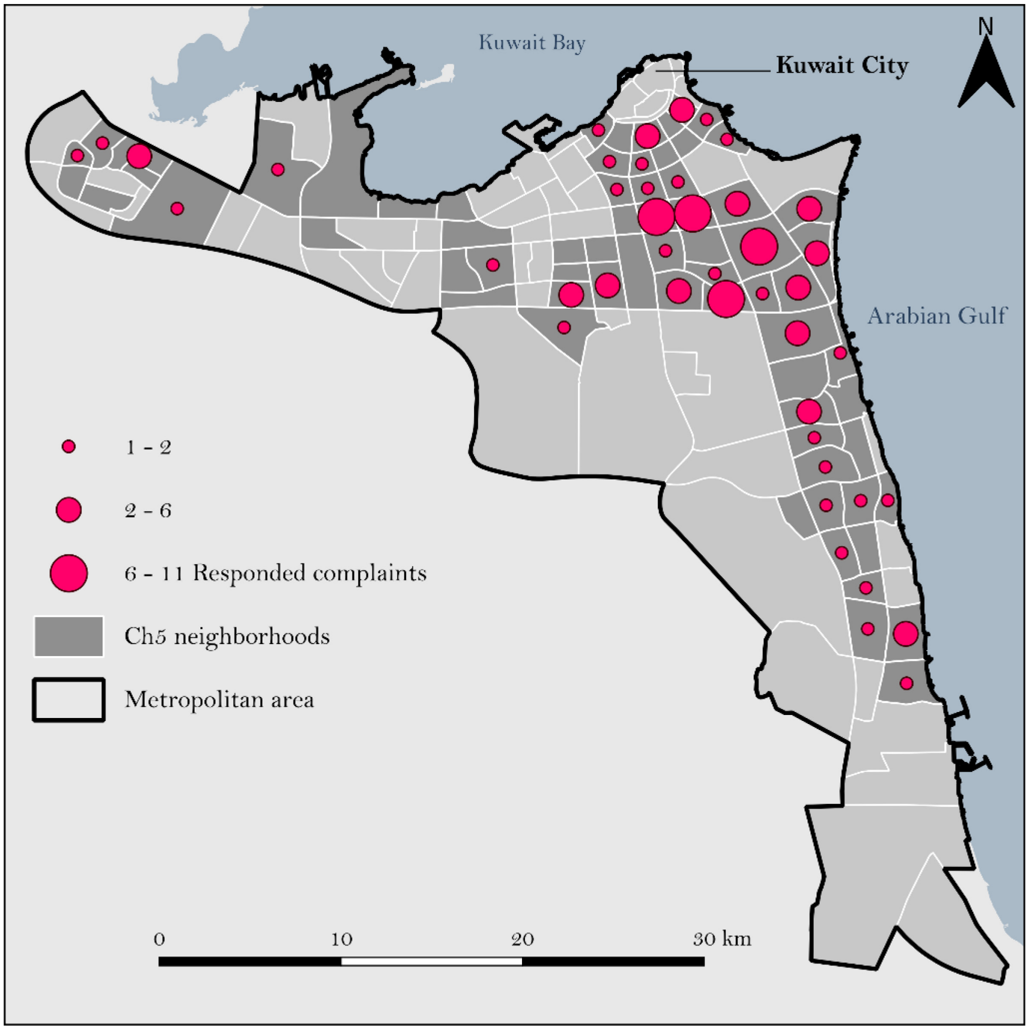


Figure 5.6. Count of responded complaints at chapter 5 neighborhoods.

Table 5.3 provides descriptive statistics on government response time for the set of resolved complaints mapped in Figure 5.5, followed by a histogram of response time in Figure 5.7. The rate of all resolved complaints within the metropolitan area is shown in Figure 5.7A, whereas Figure 5.7B narrows the summary to the 69 residential neighborhoods featured below in the regression analyses. The two patterns are essentially identical, with most resolutions coming within a week and a handful of cases that exceed that timeframe. The most frequent response time was between two and four days. The normalized responded complaints per 100 complaints (total responded complaints / total complaints * 100) and the averaged responsiveness time for each neighborhood are mapped in Figure 5.8.

Table 5.3. Comparative descriptive statistics of the responsiveness time in days.

	Count of neighborhoods	Mean	Median	Standard deviation	Minimum	Maximum
All responded complaints within the metropolitan area	67	4.1	3.5	2.9	1	16
Responded complaints within the ch5 neighborhoods	44	3.9	3.3	2.9	1	16

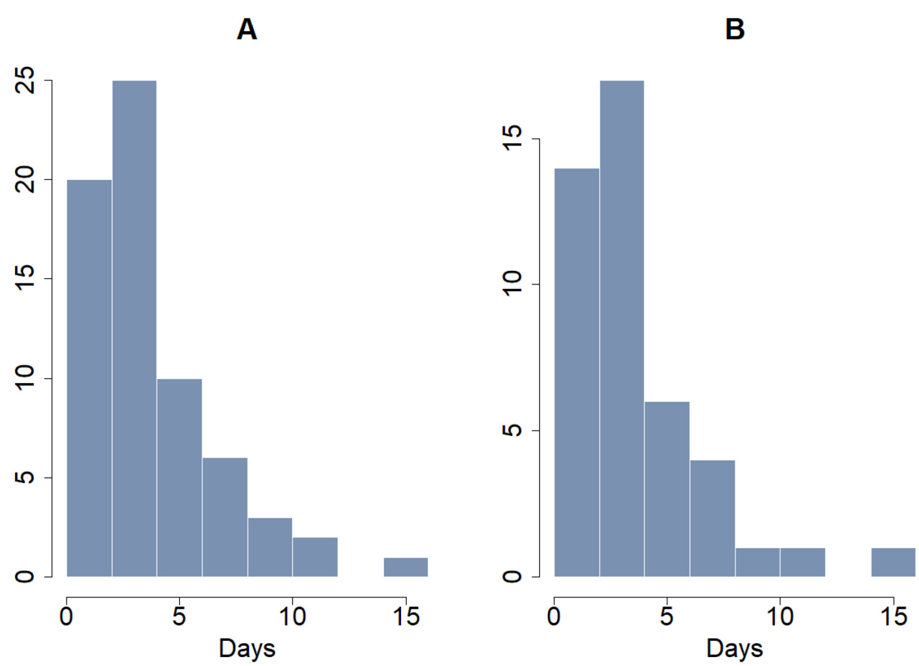


Figure 5.7. Histogram of complaint's responsiveness in days. (A) represents all neighborhoods with responded complaints, and (B) represents chapter 5 neighborhoods with responded complaints.

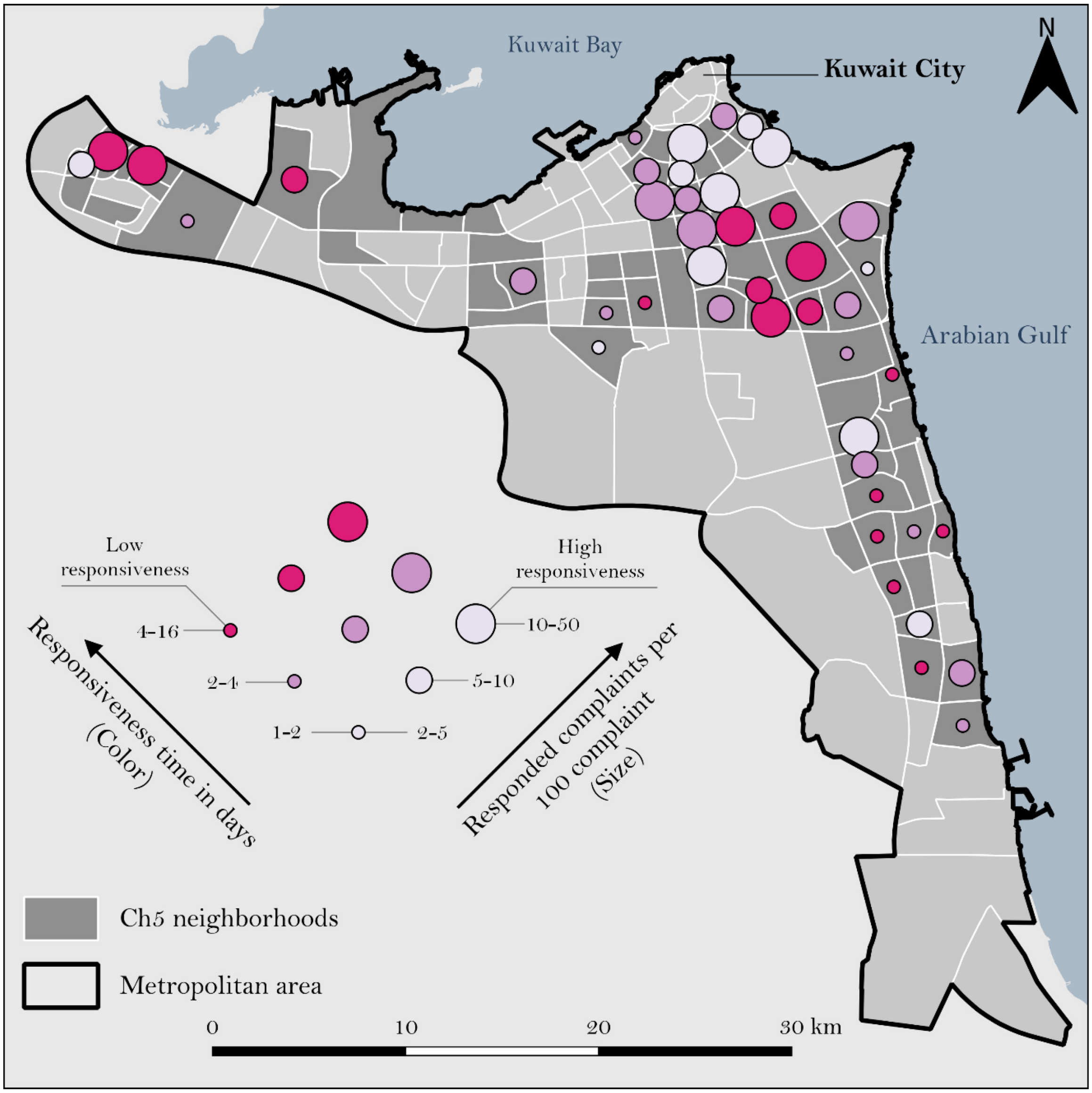


Figure 5.8. Normalized responded complaints and averaged responsiveness time in days. Symbol size illustrates responded complaints per 100 complaints frequency, while the color represents the time in days. Larger symbols indicate more responses, and lighter shades of color indicate a faster response and vice versa.

From Figure 5.8, larger symbols with lighter color shades show high responsiveness, while the smallest and darkest symbols represent poor responsiveness. Most cases of poor responsiveness occur in the southern portion of the study area, while neighborhoods near Kuwait City had among the highest responsiveness (presumably due to the proximity of these neighborhoods to the government agencies to which complaints are forwarded).

Factor analysis results

Before performing the *FA*, the number of factors to be retained in a factor solution was evaluated in a parallel analysis. The results are graphed in the scree plot in Figure 5.9, which shows that a six-factor solution is appropriate for the residential neighborhood-level socioeconomic and demographic variables. The factor loadings from extracting six factors using orthogonal rotation and principle factor solution extraction are presented in Table 5.4.

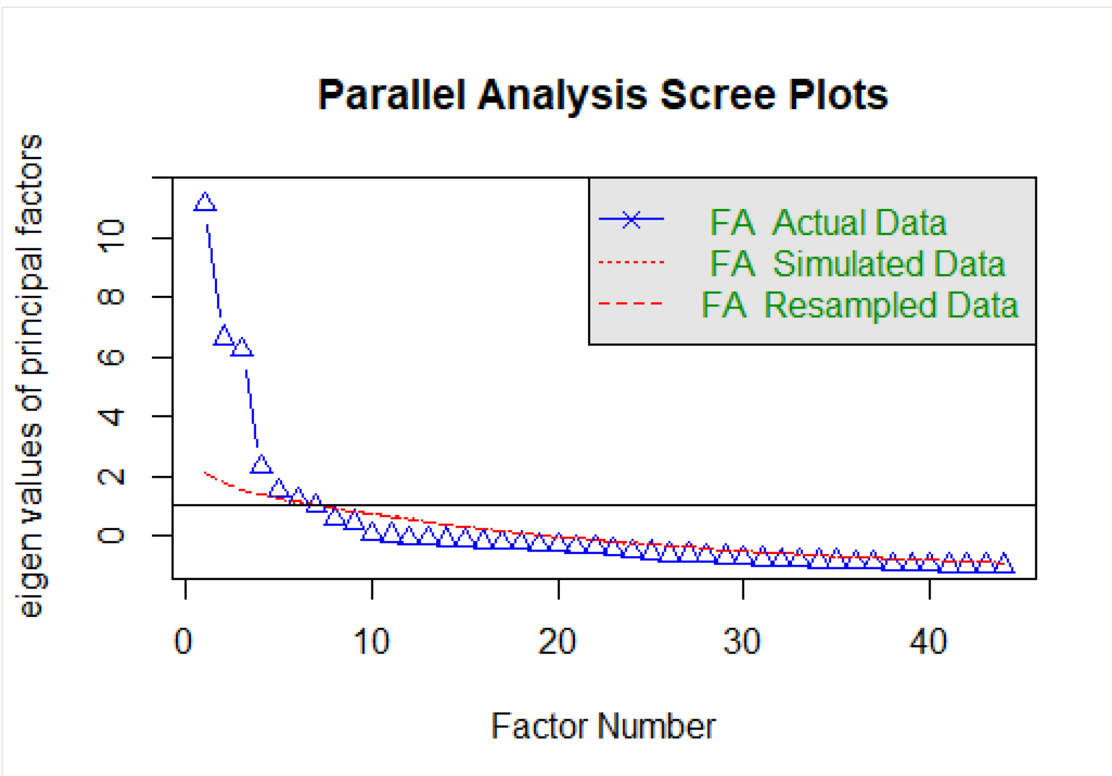


Figure 5.9. Factor analysis scree plot.

Table 5.4. Factor loadings results. The factor cutoff for the loadings = 0.3.

Variable	FA1	FA2	FA3	FA4	FA5	FA6
Population density		0.43	-0.40	-0.39		
Male	-0.92					
Female	0.92					
Age 20-29	0.55					-0.50
Age 30-39	-0.78					
Age 40-49	-0.58		0.31	0.51		
Age 50-59	-0.45		0.50			
Age above 60			0.61			
Kuwaiti	0.95					
Non-Kuwaiti	-0.95					
Never married	0.47	-0.33	0.34	0.41		-0.45
Married	-0.90		0.32			
Divorced	0.46		0.40	0.50	0.32	
Widowed	0.41		0.59			
Arabian Gulf	0.46		-0.65			
Arabian	-0.62	0.45				
Asian	0.35	-0.49	0.46			-0.33
African	0.72			0.37		
European			0.31			0.44
North American				0.77		
South American	0.49		-0.53			
Australian				0.88		
Illiterate		-0.31				0.54
Literate	-0.39	-0.79				
Elementary	0.34		0.31		0.58	
Middle			-0.80			
Secondary		0.57	-0.40	-0.31	-0.45	
Above secondary		0.53				
University and Above		0.67	0.33			
Computer usage		0.99				
No computer usage		-0.99				
Internet usage		0.98				
No internet usage		-0.98				

Variable	FA1	FA2	FA3	FA4	FA5	FA6
Averaged family size	0.77			-0.36		
Family size < 5	-0.96					
Family size 5-9	0.73					
Family size > 9	0.72			-0.33		
Labor Kuwaiti						
Labor non-Kuwaiti				-0.50		
Labor Kuwaiti male					0.70	
Labor Kuwaiti female					-0.78	
Labor non-Kuwaiti male				-0.72		
Labor non-Kuwaiti female			0.42		-0.43	
Real estate averaged price			0.86			

FA1 explained 25.3% of the variance, FA2 explained 16%, FA3 explained 11.9%, FA4 9.5, FA5 6.1, and FA6 4.3% of the variance in the 44-variable correlation matrix. Together, these factors explained 73.2% of the cumulative variance. Based on the patterns of loadings shows in Table 5.4, I offer the following interpretations/descriptions of the six factors ("Fa's"):

- **Fa1:** Significant presence of young, single Kuwaiti females, persons of mixed nationalities, lower educational attainment, and larger family sizes.
- **Fa2:** Higher population density with married couple households of mixed nationalities and high levels of education and technological usage.
- **Fa3:** Low population density of mid- to older residents of mixed marital status, mixed nationalities, mixed education levels, and high average real estate prices (i.e., income).

- **Fa4:** Low density neighborhoods with a strong presence of middle-aged, unmarried persons of mixed nationalities, sorted into smaller sized households, and few non-Kuwaiti laborers.
- **Fa5:** Single, less-educated population with a high proportion of Kuwaiti male laborers.
- **Fa6:** Married, poorly educated householders from older age cohorts.

Based on these descriptions, higher scores for Factors 2 and 3 tend to indicate affluence, high human capital, and, presumably, greater access to the technologies and skills needed to register complaints to an online SM account. Higher scores on Factor 1 might indicate a specific type of barrier to registering complaints: household management. Namely, to the extent that high Factor 1 scores describe populations of younger, single females in large households, residents from neighborhoods with these characteristics will plausibly have to expend more time an energy on maintaining household affairs, leaving less time for maintaining the urban commons. Higher scores for Factors 5 and 6 might indicate the presence of other types of barriers to participating in co-production of the urban commons (Ch. 2). Concerning Factor 5, a poorly educated working-class population may be underprepared to use SM or similar technologies for initiating contact with government. While the same educational barrier might hold for neighborhoods with high Factor 6 scores, these latter neighborhoods face an additional barrier of age. As described in Chapter 3, nearly nine of every ten SM users in Kuwait is between 18- and 44-years-old. Older populations are therefore under-connected to SM channels that would allow residents to register complaints. Finally, higher Factor 4 scores are perhaps the most neutral and indicative of something analogous to a middle-class suburb in the U.S., with lower residential densities, smaller household sizes, and middle-aged residents. Unlike for the other factors, there are neither glaring barriers to nor opportunities for participating in urban commons maintenance through communicating indirectly with government agencies via a centralized SM account.

Having identified and interpreted six factors obtained by leveraging inter-correlation in a matrix of 44 candidate socioeconomic and demographic independent variables, factor scores were obtained for each neighborhood on each factor and used as predictors in three *MR* models to answer the three research questions posed in this chapter.

Multiple regression results

MR was implemented three times – one for each of three dependent variables implicated in the three research questions (complaint volume, response volume to complaints, and response time). The results of all three regression models are summarized in Table 5.5.

For the first model (complain volume), FA2 was the only significant predictor. Recall that Factor 2 is a measure of neighborhood-level affluence and access to technology. This factor takes on a direct, significant relationship with complaint volumes.

For model #2 (complaint response volume), four of the six factors took on statistically significant relationships with the dependent variable (FA1, FA2, FA3, and FA6). Recall that two of those four factors were associated with different types of distress or barriers to participation (FA1 described large households and FA6 older, poorly educated residents); while the other two spoke to different types of affluence (FA2 indicates high technology access in dense urban areas, and FA3 indicates wealthier households in lower density neighborhoods). Both barrier/distress measures varied inversely with complaint response rates, whereas both affluence measures varied directly with the dependent variable.

Finally, in the third model (response time), FA1 and FA3 attained statistical significance. The former – again a measure of distress – varied positively with response time, meaning that higher FA1 scores were associated with longer responses. Conversely, FA3, a measure of affluence, varied negatively with response time, meaning that higher FA3 scores were linked to shorter response times (and, thus, quicker complaint resolutions).

Table 5.5. Regression coefficients for all dependent variables.

	Complaint volume		**Response volume**		**Response time**	
	Estimates	Prob>ChiSq	Estimates	Prob>ChiSq	Estimates	Prob>ChiSq
Intercept	3.4622482	<.0001*	0.5211861	0.001*	1.3610627	<.0001*
FA1	-0.049042	0.3361	-0.161291	**0.0131****	0.1012471	**0.0427****
FA2	0.2248117	**0.0061***	0.2046359	**0.0375****	-0.087217	0.279
FA3	0.0878315	0.0553	0.1759643	**0.0026***	-0.092406	**0.0436****
FA4	0.0839045	0.2341	0.031141	0.7417	0.0536674	0.4831
FA5	-0.04838	0.5319	0.0958269	0.3294	-0.035991	0.5394
FA6	-0.062351	0.3045	-0.186157	**0.0196****	0.0607311	0.283

* Significant at 0.01

** Significant at 0.05

Discussion

The purpose of this chapter was to identify the socioeconomic and demographic factors that vary systematically with observations of citizen-government interactions in

Kuwait. Research question 1 studied the degree to which neighborhood-level variation in citizen-initiated complaints can be explained by socioeconomic and demographic factors that lead to digital divides in society – providing some privileged groups with the skills, education, and resources needed to acquire and use communications technology, while barriers stand between these technologies and less privileged groups (Kuk 2003).

Research questions 2 and 3 then studied variation in local government responses to complaints and in government response time to evaluate whether government attention to complaints is equitable across different types of neighborhoods.

In answering the first question via a multiple regression model in which the dependent variable was the complaint volume and the independent variables were six socioeconomic and demographic factors, I found that higher values of a factor associated with high income urban neighborhoods were positively associated with social media (SM) complaints to the Q8needsyou group in ways that cannot be explained by chance alone. Neighborhoods with high values of this factor had relatively high population density, more married couple households, relatively high educational attainment, and high computer and internet usage. Despite coming from analysis of an ad hoc, volunteer, SM-based complaint system in Kuwait, these findings are remarkably consistent with findings from studies of 311 systems in the U.S. and other global North nations. For instance, Kontokosta, Hong, and Korsberg (2017) found that neighborhoods with more married couples tend to report to 311 more often. These same authors, as well as Lu and Johnson (2016), also found that education varies directly with the propensity to report to 311. However, there is at least one exception to this relationship, as Cavallo, Lynch, and Scull (2014) found that higher education was linked to fewer 311 reports in San

Francisco, California.) One finding that might depart slightly from the U.S. literature involves nationality. Specifically, Minkoff (2016) found a greater propensity for 311 reports in less diverse neighborhoods. In contrast to this, the significant factor revealed in the regression model for research question 1 is characterized not only by affluence and high technology use, but also by mixed nationalities. In other words, higher FA2 values speak, at least to some degree, to demographic diversity. Consequently, my regression results offer some emerging evidence that, in Kuwait, diverse neighborhoods may have a greater predisposition toward maintaining the urban commons than more homogenous neighborhoods, at least in terms of submitting concerns to a SM account. This finding contrasts with U.S.-based evidence that more ethnically homogenous neighborhoods tend to form greater levels of "social capital" that contribute to maintenance of the urban commons (e.g., Weaver et al. 2016).

Overall, then, the findings for research question 1 are mostly compatible with the 311 literature, with the exception of the possible of the diversity-related result just described. More generally, though, the significant association between affluence, technology access, technology use, and complaint rates imply the presence of a digital divide in Kuwait, where neighborhoods with a highly educated population and increased usage of technology have higher chances to report complaints (e.g., (Goldfarb and Prince 2008).

Having said that, areas that lie in the shadows (under-report) due to lack of technology skills should gain more attention from local authorities. Therefore, this finding converges with the first recommendation in Chapter 4 where governmental resources should be allocated based on the complaint's patterns and the digitally divided areas to reduce the inequalities in sharing complaints.

The findings of research question 1 extend the motivation to share complaints derived by territoriality and co-production, as discussed at the end of the previous chapter. In Kuwait, the digital divide has delineated both concepts. It seems that the sense of owning the place is a function of higher education and technological skills, suggesting that there might be inequality in territoriality motivations. If that is the case, it would be assumed that areas with lower skills exhibit a lower sense of territoriality, and they are more of a public service consumer than co-producers. However, these results are dependent on the data used that has several limitations, which will be discussed in the conclusion section.

Next, research question 2 examined the relationships between government responses to complaints and the same neighborhood-level socioeconomic and demographic factors discussed above. Regression model 2 identified four factors as significant predictors of government response to neighborhood complaints. Two of those factors – FA1 and FA6 – vary negatively with government response. Recall that those two factors measure somewhat distinctive types of economic disadvantage. Higher values of FA1 describe neighborhoods where households are relatively large, potentially headed by younger single females, and where educational attainment is low. Higher values of FA6 describe neighborhoods with older, poorly educated residents. In both situations, neighborhoods contain underprivileged residents who might lack the skills, resources, information, or, importantly, political capital necessary to compel the government to act in response to a complaint. This relative lack of neighborhood-level political power makes it difficult to hold governmental agencies or officials accountable for being responsive to citizen requests (Flora, Flora, and Gasteyer 2016).

On the opposite end of the spectrum, both FA2 and FA3 varied directly with governmental responsiveness, and both are measures of different types of affluence. Higher values of FA2 describe dense urban neighborhoods where residents are well educated and skilled/experienced technology users. High values of FA3 describe lower density neighborhoods with traditional households (married couples) characterized by high average income. While these two neighborhood types differ in their form and character, both presumably have and can exercise power. Educated urban dwellers with proficient technology skills can mobilize large numbers of residents to call attention to the same issue, thereby wielding "people power" to hold governments accountable for being responsive (e.g., Engler and Engler 2017). And relatively wealthy households arguably have status and political power that encourages governments to assign extra "weight" to the complaints such households make – thereby leading to increased responsiveness (e.g., (Fischel 2001).

In the above respects, the findings from Kuwait echo observations on citizen-government relations made with U.S. and other western nations. Namely, being on the more affluent side of the digital (and social/economic) divide ostensibly translates into political power and the ability to influence government decision-making; and being on the disadvantaged side of those divides is disempowering, characterized by a relative inability to influence public actions and decisions (e.g., (Wright and Rogers 2015).

Finally, research question 3 built on the immediately preceding findings by studying government response time to complaints (in days), rather than mere response levels. The from these regression model reinforced the findings from research question 2. Specifically, two factors were significant predictors of response time. The first significant predictor, FA1, is once again a measure of a type of disadvantage. High FA1 values signify neighborhoods with large household sizes, low education levels, and potentially single heads of household. Just as model 2 discovered that such neighborhoods are less likely than more affluent neighborhoods to realize resolution to their SM complaints, even when complaints are responded to, response times are longer than in other neighborhoods. That is, the positive relationship between response time and FA1 indicates that as FA1 values increase, so does government response time. The upshot is that high-FA1 neighborhoods see fewer resolutions to their complaints (model 2), and they wait longer when government actions are eventually taken (model 3).

Oppositely, the negative relationship between FA3 and response time suggest that more affluent neighborhoods benefit from faster government responses. More precisely, recall that FA3 is a measure of affluence that describes wealthier family households in lower density communities. Just as wealthy, upper-class suburban communities in the U.S. tend to enjoy ample political power (Fischel 2001), high-FA3 neighborhoods in Kuwait benefit from both greater government responsiveness to SM-generated complaints (model 2), *and*, as identified in the analysis for research question 3, shorter wait times for government responses (model 3). As was the case with model 2, these results are quite compatible with observations on U.S. society (Wright and Rogers 2015).

Because research questions 2 and 3 essentially investigated the same phenomenon (government responsiveness to complaints) in two ways (through response volume and response time), it is helpful to clarify the similarities and differences between them. Table

5.6 performs this function by summarizing the key findings from each model side-by-side.

Table 5.6. Research questions 2 and 3 comparative summary.

Socioeconomic and demographic theme	Response volume	Response time
Population density	Increase with higher density	Faster with a high population density
Male Gender	Increase	Faster
Age	Increase with older groups	Faster with younger groups
Citizenship	Increase with higher non-Kuwaiti	Faster with non-Kuwaiti citizenship
Nationality	Mixed*	Mixed*
Marital status	Increase with married population	Faster in unmarried population
Education	Increase with higher education	Faster with high education
Technology	Increase with higher usage	N/A*
Family size	Increase with small family size	Faster with small family size
Labor	Increase with higher non-Kuwaiti	Faster with non-Kuwaiti labors
Real estate price	Increase with higher prices	Faster with high prices

* No specific explanatory variable was identified.

** No significant findings. The explanatory variables were not significant in the identified factors.

Conclusion

Research on 311 systems in the U.S. and other nations of the global North consistently finds that the propensity for citizens to register complaints to such systems – and thus to engage in co-production of the urban commons – reflects broader patterns of social and economic inequality that are sometimes captured in the concept of digital divide (Ch. 2). In short, lack of access to education and technology (among other opportunities), which correlates with low income and disproportionately affects persons of color, produces uneven patterns of 311 participation. Invariably, more affluent, homogenous neighborhoods tend to register more complaints. Reinforcing these patterns, affluent neighborhoods tend to wield greater political influence. This phenomenon translates into something of favoritism, with governments acting more responsively toward neighborhoods on the upper end of economic and digital divides, and less responsively toward neighborhoods at the bottom end of these divides (e.g., (Wright and Rogers 2015).

Given the lack of 311 or 311-like systems outside of the global North, there is little research on whether these relationships hold elsewhere. Using data from a quasi-311 system run by volunteers through a SM account, this chapter found that many of the same uneven patterns that characterize U.S. non-emergency complaints do in fact hold in Kuwait. On the whole, better educated and more affluent neighborhoods register more complaints, which, coupled with their higher social status, seems to give those neighborhoods disproportionate political power. Concerning the latter, government responsiveness – in terms of both volume and response time – shows evidence of bias toward neighborhoods with well-educated, high income residents who are proficient technology users. One opportunity for future research is to further explore the role of diversity in urban commons maintenance in Kuwait and other international contexts. Unlike in the U.S., where ethnic diversity often undermines co-production of the urban commons (Weaver et al. 2017), the regression analyses in this chapter uncovered emerging evidence that neighborhoods characterized by residents with mixed nationalities might use SM channels to interact with government at higher levels than more homogeneous neighborhoods. Another opportunity for follow-up research is to analyze government responsiveness by complaint type. It is possible that the unevenness in government responses observed in regression models 2 and 3 might disappear for certain types of complaints that require immediate resolution (consider the example of a power outage, which threatens public health and safety).

In addition to these extensions, there are several opportunities to address key limitations with the analyses presented above, including the following:

- **Census data were from 2011**: the gap between social media (SM) posts and Kuwait's full census is eight years. Using updated census data, when available, will provide more timely results.
- **No household mean income measurement**: income data are used extensively in U.S.-based literature. Recall, however, that no such data exist in Kuwait. As an alternative, real estate prices were used. Using the average price of private housing limited the sample size for the analysis by excluding neighborhoods where these data were not available.
- **Spatial scale**: the study was carried out at the neighborhood level. It would be possible to perform the analysis at the blocks level. However, real estate data are only available at the neighborhood level. Working to identify other income proxies at the block level would allow the research to be replicated at a finer resolution.
- **Addition of buildings data**: integrating data on the built environment (e.g., year a structure was built) would add valuable insights to these analyses. In the U.S., there is clear evidence that 311 complaints are regularly made against older, less well-kempt structures (Weaver 2013). Accounting for these aspects of the built environment would arguably explain more variability in the patterns of complaints.
- **A limited sample of resolved complaints**: of all the complaints made in 2019, only 270 (7.6%) were resolved. When the data are limited to

predominantly residential neighborhoods, there were only 131 resolved complaints in the dataset. Increasing the sample size by scraping data for more years would be a valuable exercise.

Finally, future research that compares complaint patterns and government responsiveness patterns by communication channel would be a major contribution. Such a study would involve obtaining complaint data made through traditional channels (phone call or face-to-face visit) from authoritative agencies and structuring that data in much the same way as the design shown in Figure 3.10. With that data, it would be possible to design and execute a comparative analysis to understand whether the biases observed in the SM complaint models also exist in complaints from traditional sources, among other research questions.

6. GEOVISUALIZATION OF CITIZEN-GOVERNMENT INTERACTION

Chapters 4 and 5 examined the spatial nature of citizen complaints to characterize the spatial patterns of complaints and explore the extent to which those patterns are systematically related to socioeconomic and demographic attributes. In this chapter, advanced geovisualization methods were implemented to gain further insights through visual exploratory analysis. The visualization approaches used in this chapter explored the multivariate nature of the data and the interconnectivity at the intra-governmental level (i.e., agencies). In the literature, maps and other visualization methods are regularly deployed as tools to present the results; but they are rarely considered to be an objective of the research. This chapter takes the latter approach. Namely, the objectives of this chapter were to:

1. Implement multivariate mapping methods to identify spatial clusters of citizen-government interaction characteristics at the neighborhood level.
2. Implement geovisualization methods for agency interconnectivity at the country and governorate level.

For objective 1, two multivariate mapping techniques were implemented: (1) bivariate and (2) multivariate mapping. Further details about both methods are provided in the following background section. Regarding objective 2, geovisualization dashboards for agency interconnectivity were implemented at both country and governorate level.

The next section provides a gentle background on thematic and multivariate cartography, followed by a review on visualization methods used in the literature. Subsequently, data design and methods are described, followed by a presentation of results, discussion, and conclusion.

Background

Thematic and multivariate cartography

Graphics are means for communicating and transporting knowledge, and the graphic representation for communicating geospatial information is called a *map* (Robinson et al. 1995). Maps are generally categorized into general reference maps and thematic (or statistical) maps (Robinson et al. 1995; Dent, Torguson, and Hodler 2009; Slocum et al. 2009). General reference (or purpose) maps are used to emphasize the location of spatial features such as topographic maps. On the other hand, thematic maps are used to demonstrate the spatial location or pattern of geographic features with one or more variables such as population density (Slocum et al. 2009) and thus represent a geographic *theme* (Dent, Torguson, and Hodler 2009).

Thematic maps can furtherly be categorized into qualitative (e.g., geological maps) and quantitative maps (e.g., average household income) (Dent, Torguson, and Hodler 2009). Selecting the type of map depends on the map's purpose. For citizen complaints, both thematic map types can be used to communicate with the audience. For instance, the volume of service requests represents the quantitative side, and the distribution of request types represent the qualitative side. There are several methods to portray information on thematic maps including, but not limited to (Dent, Torguson, and Hodler 2009):

- **Choropleth maps**: mapping data collected in an enumeration unit (country or region).
- **Proportional symbol maps**: mapping data through symbols (usually circles) scaled to values at points.

With choropleth maps, data are normalized in the form of ratios or percentages. Using totals is misleading due to unequal areal unit sizes. To use data totals, proportional symbol maps represent a superior choice (Field 2018). As mentioned earlier, thematic maps portray one (*univariate*) or more variables. The latter type of thematic maps is called *Multivariate* maps.

Multivariate maps present simultaneously two (*Bivariate*) or more (*Multivariate*) variables (Slocum et al. 2009; Nelson 2020). Multivariate mapping is beneficial to increase the amount of information and to enable the audience to interact with the map and explore different geographic relationships. The downside of such a technique is the visual complexity of the map (Nelson 2020). Nevertheless, using multivariate mapping methods should reveal additional insights into the citizen-government interaction domain and represents an additional contribution of this research to the body of knowledge.

Visualization methods used in the literature

Multiple map types have been used in the literature to share summary information or relevant findings. Table 6.1 provides a summary of map types used in research on 311 systems. Both qualitative and quantitative maps are present in these studies. Several studies used choropleth maps to visualize 311 request quantities (Cavallo, Lynch, and Scull 2014; Minkoff 2016). Still, despite the various maps used in the 311 literature, there is little evidence that advanced multivariate mapping or geovisualization have been used to explore citizen complaints.

Table 6.1. Review of thematic maps used in the literature.

Source	Map type	Thematic map note
Schellong and Langenberg (2007)	Qualitative thematic map	Point symbol map
Cavallo, Lynch, and Scull (2014)	Quantitative thematic map	Choropleth map
Eshleman and Yang (2014)	Qualitative thematic map	Point symbol map
Lu and Johnson (2016)	General reference and quantitative thematic maps	Choropleth map
Minkoff (2016)	Quantitative thematic map	Choropleth map
Kontokosta, Hong, and Korsberg (2017)	Quantitative thematic map	Choropleth and hotspot maps
Wang et al. (2017)	Qualitative thematic map	Areal clusters map
Xu et al. (2017)	Quantitative thematic map	Choropleth, point, and density maps

Regarding the second objective for this chapter, another underexplored opportunity is using *geovisualization* and network visualization to uncover latent associations in citizen complaint data. Geovisualization represents the integration of scientific visualization, cartography, image analysis, information visualization, exploratory data analysis (EDA), and geographic information systems to provide theory, methods, and tools for visual exploration, analysis, synthesis, and presentation of geospatial data (Dykes, MacEachren, and Kraak 2005). In addition to geospatial representation, network visualization of agency interconnectivity represents a significant component of the geovisual method developed in this chapter.

In her research, Gao (2018) used *Social Network Analysis* (*SNA*) to identify both actors and the nature of their connection via 311 tweets collected from five U.S. cities. *SNA* refers to the set of nodes (e.g., individuals or organizations) connected through one or more social relationship types (Marin and Wellman 2011; Himelboim, Smith, and Shneiderman 2013). Gao's (2018) innovative work analyzing network association of 311 data is an instructive study for this chapter, which seeks to extend her approach to exploring underlying relationships in citizen complaints data.

Throughout the remainder of this chapter, actors (or nodes) are defined as the governmental agencies mentioned in each social media (SM) post. Using the SM posts, it was possible to produce an *Adjacency Matrix* to visualize the network association with both connectivity (e.g., agencyA and agencyB were mentioned together in a post) and volume (e.g., agencyA is mentioned with agencyB in *n* posts). Such a matrix can be created at multiple spatial scales (i.e., country and governorate). The spatial network analysis can reveal otherwise hidden agency connections.

Data and methods

For objective 1, data were obtained at the neighborhood level, within the metropolitan area, and are outside the primary roads buffer zone. The variables used for the visualization included the complaints, complaints by gender, complaints based on nature (natural or human-based [see Ch. 2]), engagement (i.e., “likes”), responsiveness time, and season.

The data design to carry out this objective is illustrated in Figure 6.1. All the variables mentioned above were selected from the “complaints_t”, “census”, and “response_t” tables. The “neighborhoods” table was chosen to perform a spatial join to aggregate the following variables at the neighborhood level:

- Count of complaints.
- Count of $gender_i$ complaints (male and female).
- Count of $nature_i$ complaints (natural and human-based).
- Average response time in days.
- Average engagement per post.

To obtain the ratio of $gender_i$ participation, the count of $gender_i$ complaints was divided by the $gender_i$ from the census table for each neighborhood then multiplied by 1,000 (e.g., count of male posts in $neighborhood_i$ * count of males in $neighborhood_i$). The results represent the number of $gender_i$ users that share complaints out of every 1,000 $gender_i$ persons in each neighborhood. The season field in the complaints table was used to generate seasonal ratios for gender participation seasonal analysis. The same approach was followed to generate variables on the nature of each complaint. For each neighborhood, the count of $nature_i$ was divided by the complaints count to get the ratio of $nature_i$.

The following output variables were used to create the final multivariate maps:

- Average response time.
- Ratio of $gender_i$ participation (male and female).
- Ratio of $nature_i$ complaints (natural and human-based).
- Average engagement per post.

Both bivariate and multivariate maps were used to fulfill the objectives of this chapter. Bivariate choropleth maps were used to visualize any existence of gender digital participation segregation by visually examining the spatial patterns of $gender_i$ ratio during 2019 and each season. Proportional symbol multivariate maps were used to visualize six citizen-government interaction indicators (average engagement, $gender_i$ ratio, $nature_i$ ratio, and time).

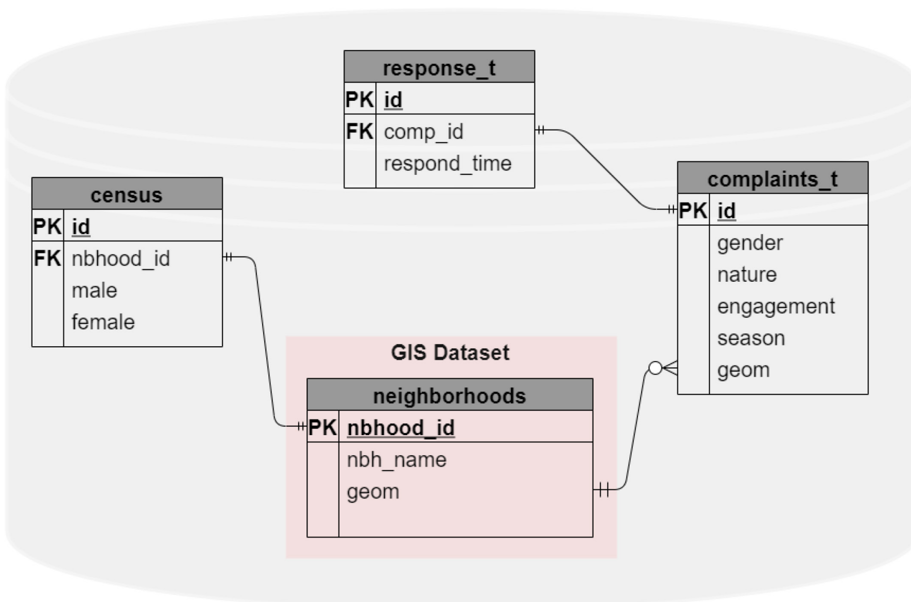


Figure 6.1. Database design of the multivariate mapping data.

Regarding objective 2, the data selected had no constraints, since it was visualized at the country and governorate level. Therefore, all complaints were included. *Chord Diagram* visualization technique was selected in this research due to its capabilities to display the relationships between the agencies and to show the magnitude of the association through the arcs (Kirk 2016). The data structure for such visualization requires an adjacency matrix with a count of occurrence between any pair of agencies. There were 33 distinct agencies mentioned by citizens in the complaints dataset. To reduce the visual complexity, the top 10 most frequent agencies were included in the analysis. The top 10 agencies are presented in Table 6.2. Based on the summary from Table 6.2, the matrices were created for the identified agencies.

Table 6.2. Top 10 most frequent agencies.

Name	Abbreviation	Count
Municipality	Mun	2666
Ministry of Interior	Moi	2327
Ministry of Public Works	Mpw	1375
Ministry of Health	Moh	455
Ministry of Electricity and Water	Mew	404
Public Authority for Agricultural Affairs and Fish Resources	Paaf	335
Ministry of Social Affairs and Labor	Msal	333
Environmental Public Authority	Epa	204
Public Authority for Roads and Transportation	Part	175
Ministry of Communications	Moc	128

The matrices were created at the national level and for each governorate. The data design for objective 2 is illustrated in Figure 6.2. Using spatial join, each complaint was assigned a governorate id (gov_id) based on the governorate it lies within spatially. Such spatial join was made between the "governorates_t" table and the complaints table using the geom fields from both tables. After assigning the gov_id, an iterative process was performed to create each matrix.

Each iterative process calculated the count of occurrence of $agency_i$ with the rest of the agencies. For each matrix, this process was repeated ten times to include all the agencies in Table 6.2. During each iteration, the count of all agencies is calculated with a condition where $agency_i$ (i.e., Municipality) is available (or not null). The result of each iteration was a row with ten fields representing the count of occurrence for each agency when, i.e., mun, was mentioned. The second iteration replaced the first agency with the second agency as described above. The final output was the desired data matrix.

For governorate matrix generation, an additional statement was included to limit the calculation by gov_id. An example of a *Structured Query Language* (*SQL*) code to calculate the matrix is presented in Figure 6.3A. The results of the query are included in Figure3B. Based on the results of the illustrative example, "mun" has occurred 124 times with "moi" in "Al-Asima" governorate. The iterative process was made in the *R* programming language environment. Once the matrices are created, chord diagrams were generated for Kuwait and $governorate_i$. Using the results, the final geovisualization dashboard consisted of five visual elements:

- Two elements on the left side of the dashboard to show the results of the country's interconnectivity.
- Two elements on the right side of the dashboard to show the results of $governorate_i$ interconnectivity, and
- A central element showing a map of Kuwait with highlighted governorate.

Both left and right elements included a chord diagram (the top element) and the matrix (bottom element). The geovisualization dashboard was created using *R Flexdashboard*.

Figure 6.2. Database design of the network visualization data.

A

```sql
-- Getting the count of occurrence for each agency
select
    count(mun) as mun, count(moi) as moi, count(mpw) as mpw,
    count(moh) as moh, count(mew) as mew, count(paaf) as paaf,
    count(msal) as msal, count(epa) as epa, count(part) as part, count(moc) as moc
from compaints_t
where
-- Selecting the count of occurrence with the first agency
    mun is not null
-- Limiting the count to specific governorate
    and gov_id = 1
```

B

mun bigint	moi bigint	mpw bigint	moh bigint	mew bigint	paaf bigint	msal bigint	epa bigint	part bigint	moc bigint
504	124	36	27	22	31	33	33	3	5

Figure 6.3. Example of the adjacency matrix calculation in SQL. (A) represents the SQL block to calculate the occurrence of each agency with agency$_i$ and (B) represents the results.

Results

Bivariate thematic mapping

As discussed in the background section, bivariate maps portray two variables on a map simultaneously. For this chapter, bivariate choropleth maps were created to visualize disparities in gender of SM complainants. Multiple maps were created to visualize the results for 2019 and each season at the neighborhood level. In cases for which neighborhood$_i$ had no data of any variable, then the neighborhood was assigned a status of “No data.” *Quantile* classification was used to create three classes (low, medium, and high) for each variable. This choice was made for visual simplicity (Stevens 2015).

The results of gender digital participation mapping are shown in Figure 6.4. In Figure 6.4, blue shades represent greater proportions of males, while red shows greater proportions of females. In 2019 (Figure 6.4A), female participation was predominant in most neighborhoods, with reasonably equal gender participation. Many cases of reasonably equal participation occurred close to Kuwait City. Male participation was mainly clustered in industrial areas around Shuwaikh Port in the north (Figure 6.4A).

Seasonal visualizations revealed several interesting patterns. First, during spring (Figure 6.4B), several areas in the east exhibited a majority-female participation. The western and southern regions had an overall balanced pattern. Areas around the Port had more male-majority participation. During the summer (Figure 6.4C), male participation was dominant in most of the study area except for some neighborhoods in the east. In fall (Figure 6.4D), an overall balance between both genders was observed. Spatially, however, complaints from males came predominantly from the center of the study area, and females made greater shares of complaints in the eastern region, similar to the summer pattern. During winter (Figure 6.4E), females were again more likely than males to make complaints in the eastern area, including now near Kuwait City. Males once again were more likely than females to register complaints around the Port and at the center of the study area.

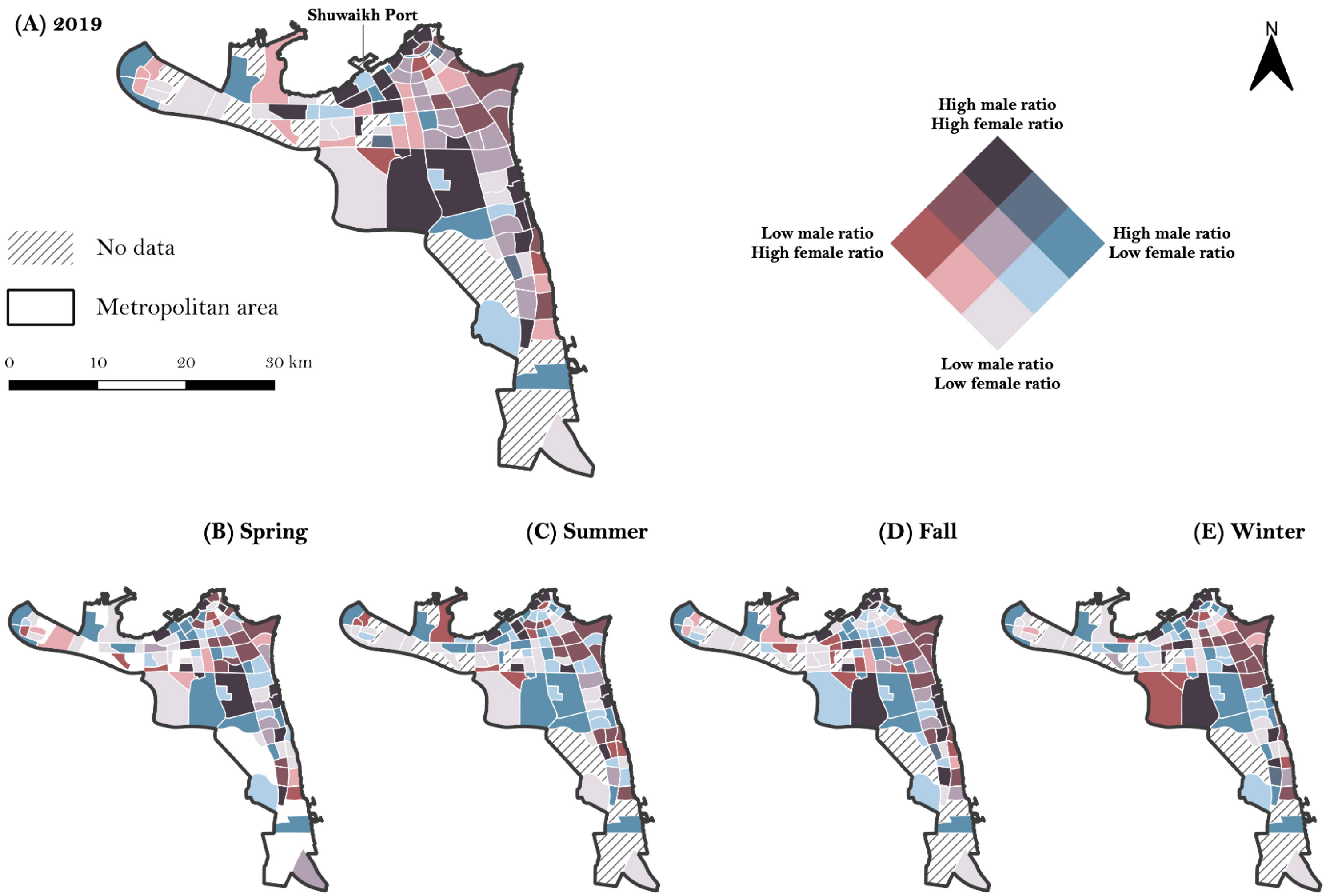


Figure 6.4. Bivariate map of gender digital participation segregation.

Multivariate thematic mapping

In multivariate maps, three and more variables are represented. In this chapter, six citizen-government interaction variables were visualized spatially using *Redundant Cues* proportional symbols. Redundant cues are cases when more than one visual dimension encodes the same data variable (Nelson 2020). Each symbol represents a variable, and it varies in size proportionally to its value. Figure 6.5 explains the legend of the multivariate map in further detail.

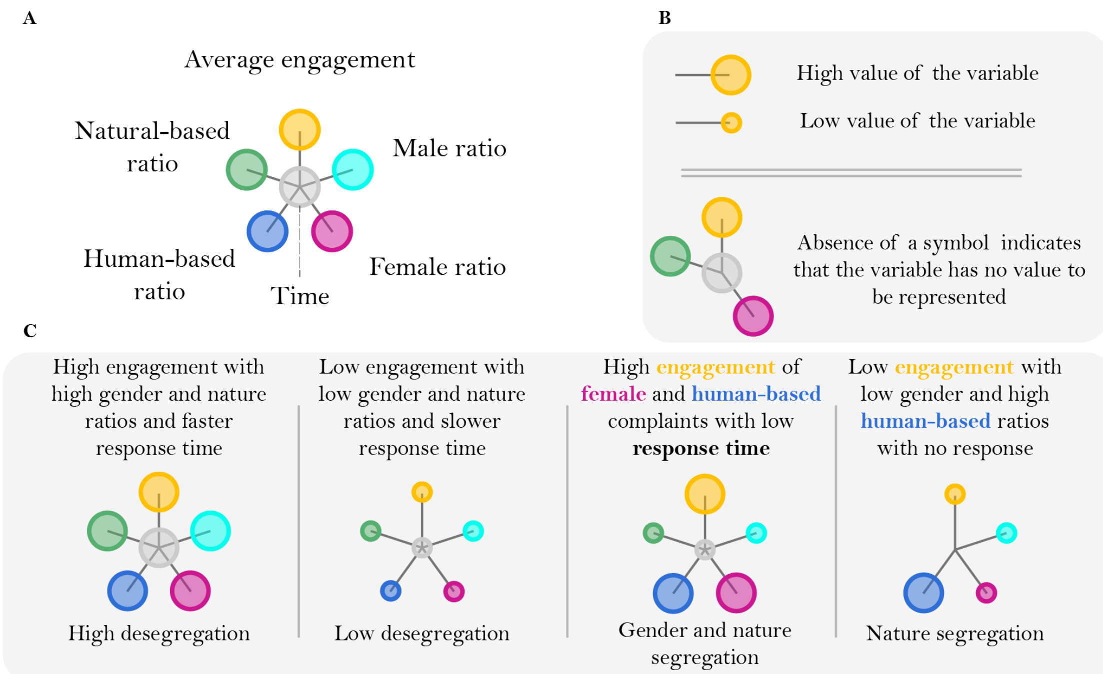


Figure 6.5. Multivariate map legend illustration.

Each of the six variables is represented with a symbol (i.e., circle), and each circle has a unique color (Figure 6.5A). The size of the circle varies based on the value each variable represents (Figure 6.5B top). Regarding data classification, the same method used in bivariate maps (quantile) was adopted to classify the data into two classes (low and high). In the case of the "Time" variable, a larger symbol indicates a faster response and vice versa. If a variable had no data, the symbol and its node were eliminated (Figure 6.5B below). To illustrate the varying conditions of the resulting map, an *Archetypal legend* was used to facilitate the process of understanding the map (Figure 6.5C). Archetypal legend is a small set of notable symbol conditions with a brief description of the interesting character of each combination (Nelson 2020). Such a legend was included in each map.

The maps were created at the neighborhood level for 2019. The results are presented in Figure 6.6. As depicted in the figure, the results are visually cluttered, and symbols were overlapped. Thus, it becomes difficult to interpret the patterns from the map. For visual simplification and clarity, the maps were subdivided into the governorate level to visualize the results at a larger scale.

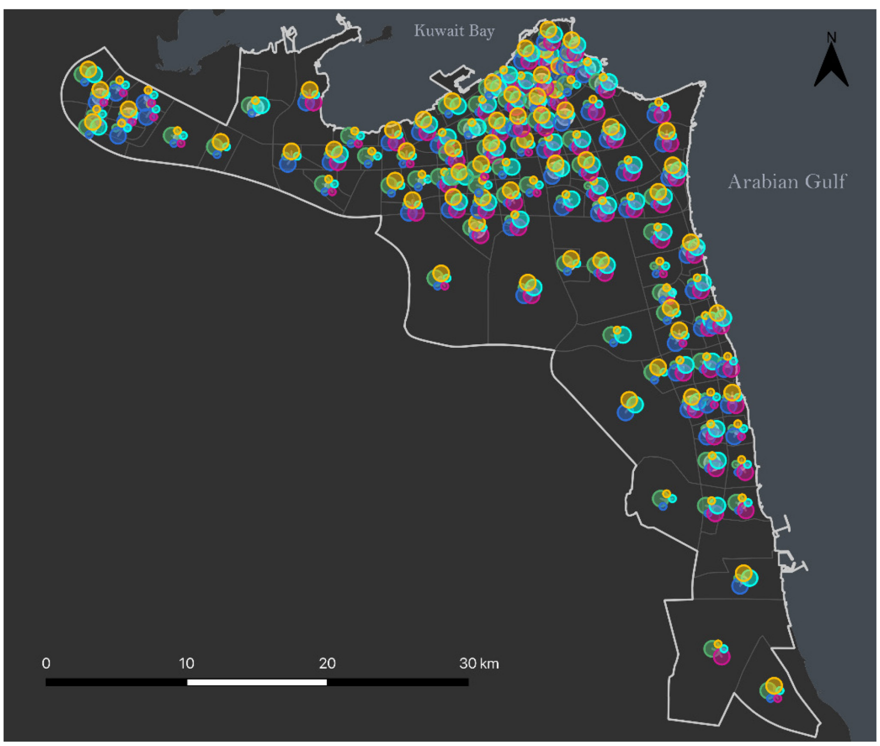


Figure 6.6. Multivariate map of citizen-government variables in 2019. The clutter increases in areas around Kuwait City.

Starting with Al-Asima governorate, the results of the 2019 multivariate map are presented in Figure 6.7. Looking at average engagement, most areas around Kuwait City tend to have higher average engagement per post with less gender disparity. It was also noted that areas proximate to the City have higher nature segregation where less natural-based ratios are reported. Moving away from the City towards the west, more cases of missing variables can be detected. Also, most neighborhoods on the western side of the governorate had no response compared to the eastern side.

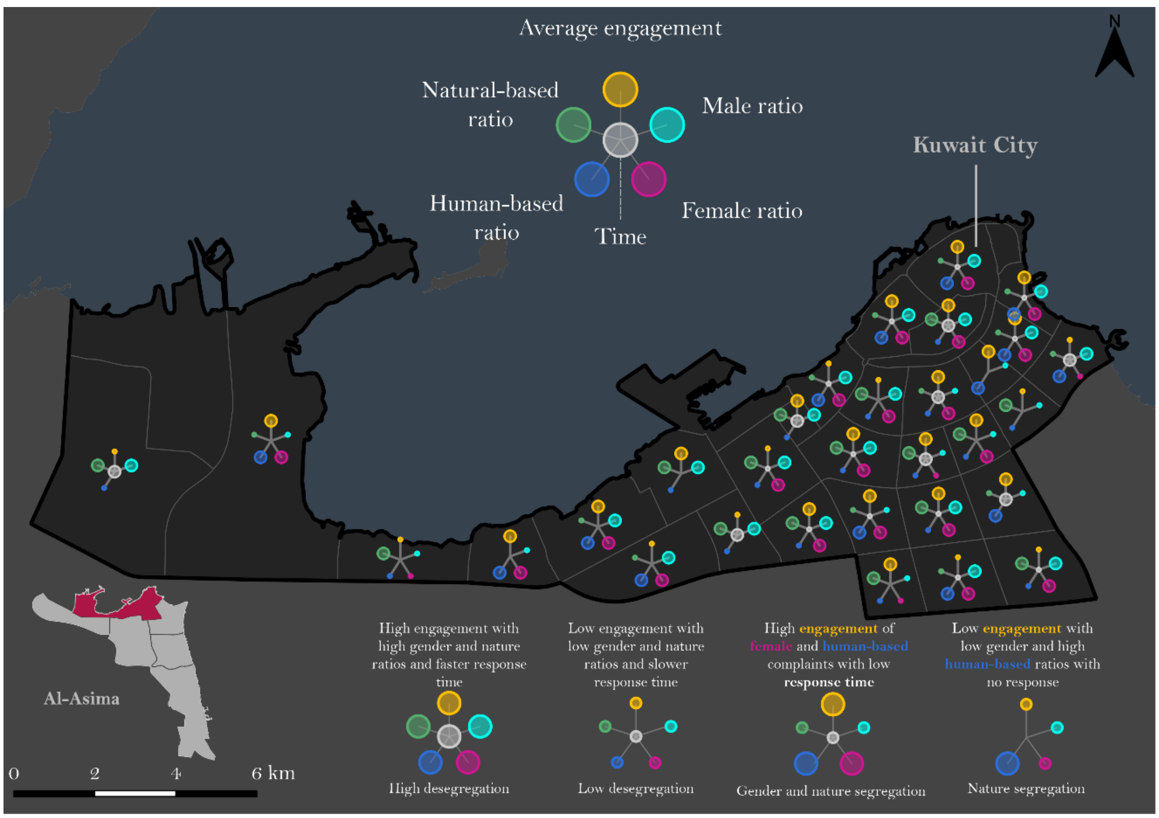


Figure 6.7. Multivariate map of citizen-government variables in Al-Asima.

The results of Hawalli governorate are presented in Figure 6.8. Overall, average engagement is balanced in this governorate. Participation is more balanced by gender in Hawalli areas. Additionally, most areas exhibited human-based complaints indicating higher incivility activities in the governorate. Finally, governmental responsiveness seems to be low in this governorate, with a majority of slower response time.

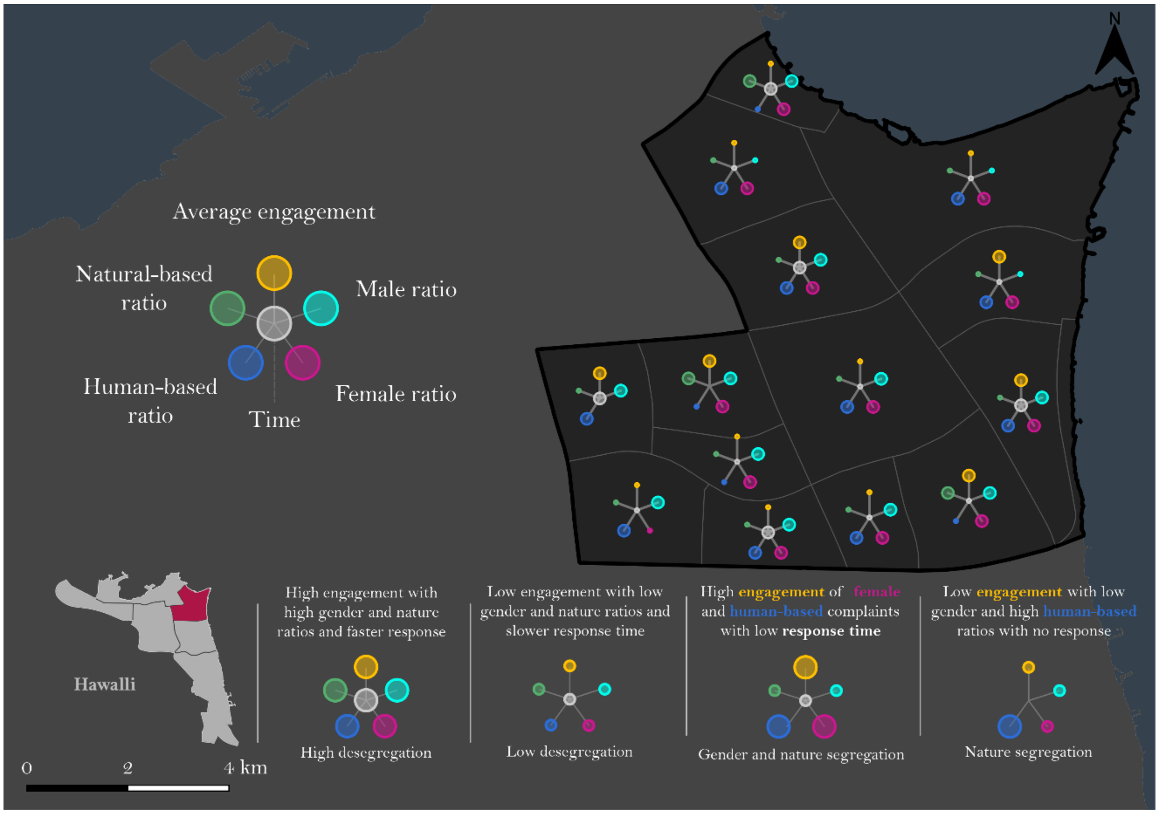


Figure 6.8. Multivariate map of citizen-government variables in Hawalli governorate.

The results of the next governorate, Al-Ahmadi, are illustrated in Figure 6.9. The average engagement with complaints in this governorate was low in general. There were gender disparities in about half of the areas, characterized by higher female participation. There was no clear propensity to report either natural or human-based complaints, and both were balanced in Al-Ahmadi. There were more responded cases in this governorate, and most responses were slow. It was also observed that areas at the western and southern borders had no responses.

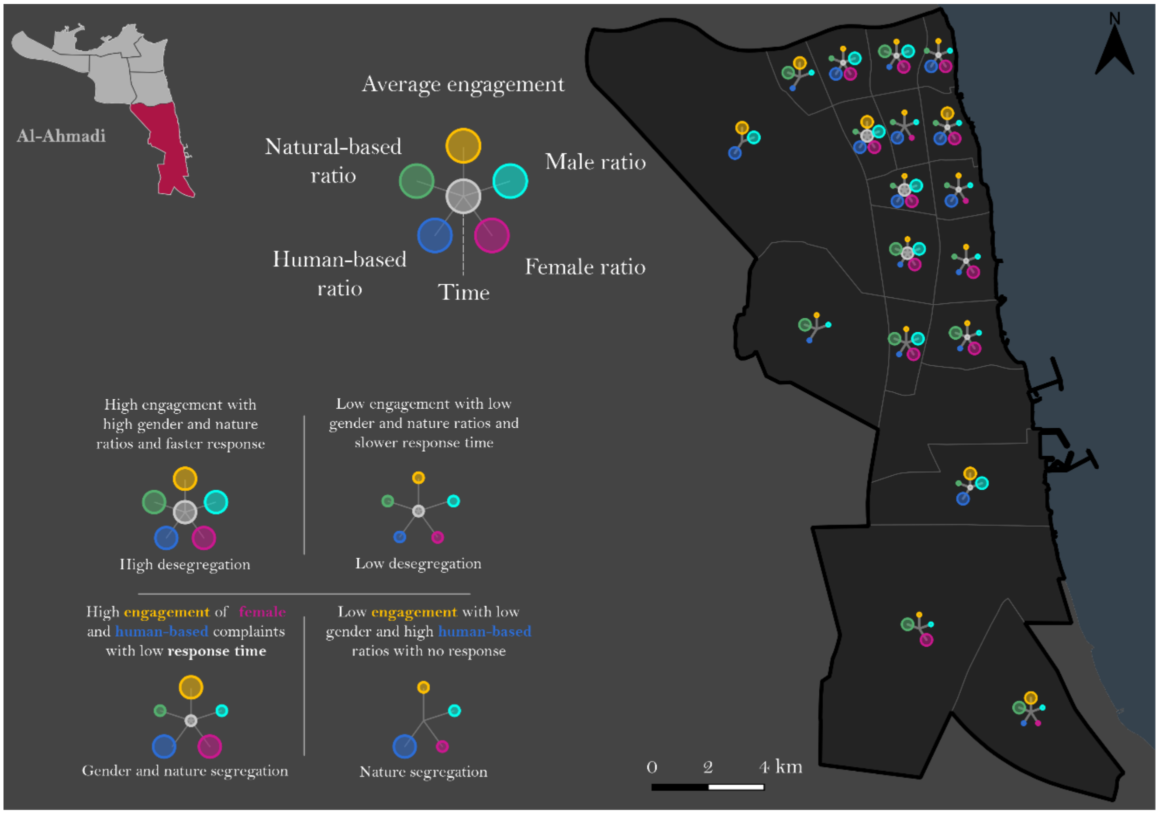


Figure 6.9. Multivariate map of citizen-government variables in Al-Ahmadi governorate.

The multivariate map of Al-Jahra governorate is shown in Figure 6.10. Like Hawalli (Figure 6.8), engagement was balanced in Al-Jahra with no clear high or low engagement clusters. There were fewer gender disparities in participation, but with slightly more male participation compared to females. Like Hawalli (Figure 6.8), there are more cases of human-based complaints compared to natural-based. In terms of responsiveness, about half of the governorate areas received responses, mostly located in the western areas. In addition, responses were generally slower in Al-Jahra.

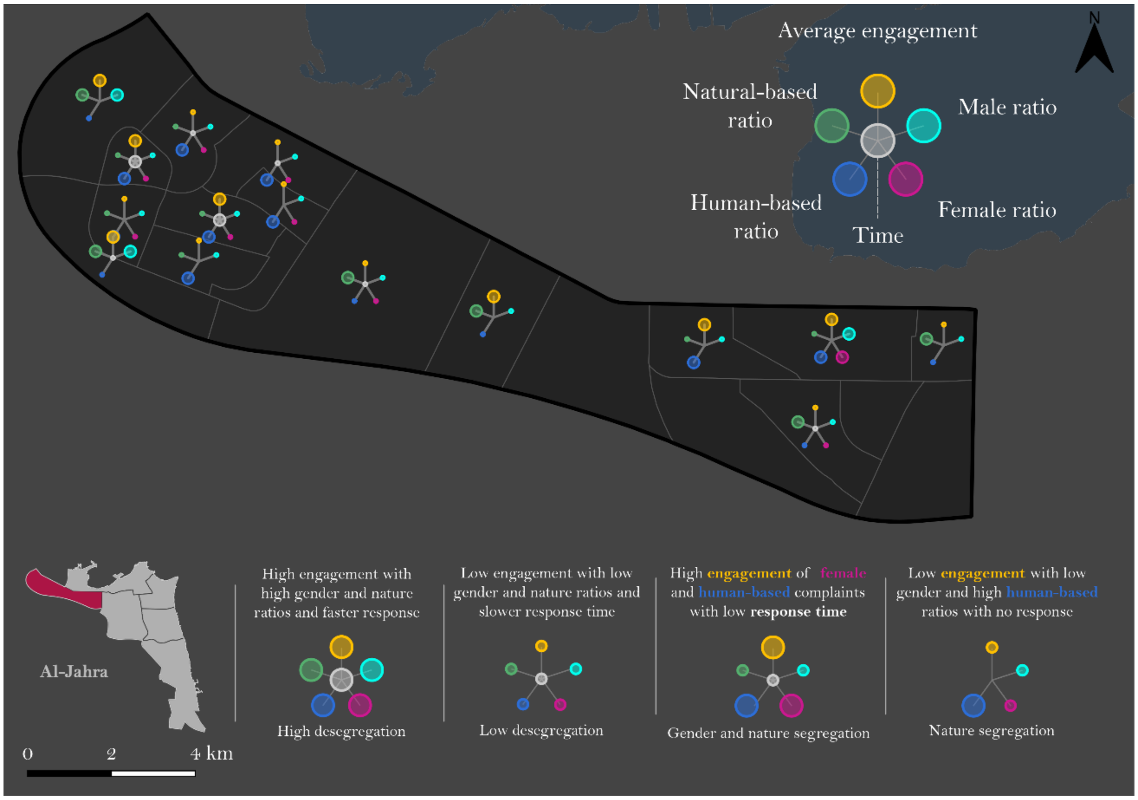


Figure 6.10. Multivariate map of citizen-government variables in Al-Jahra governorate.

The results of Al-Farwaniya governorate are demonstrated in Figure 6.11. The average engagement to complaints was high in most neighborhoods. There were relatively balanced levels of participation by gender. Most complaints were based on natural deterioration (natural-based), and human-based complaints can be found at the center of the governorate. Responsiveness to complaints was low, where most areas had no or slow response to complaints. Such areas can be observed mostly at the center of the governorate.

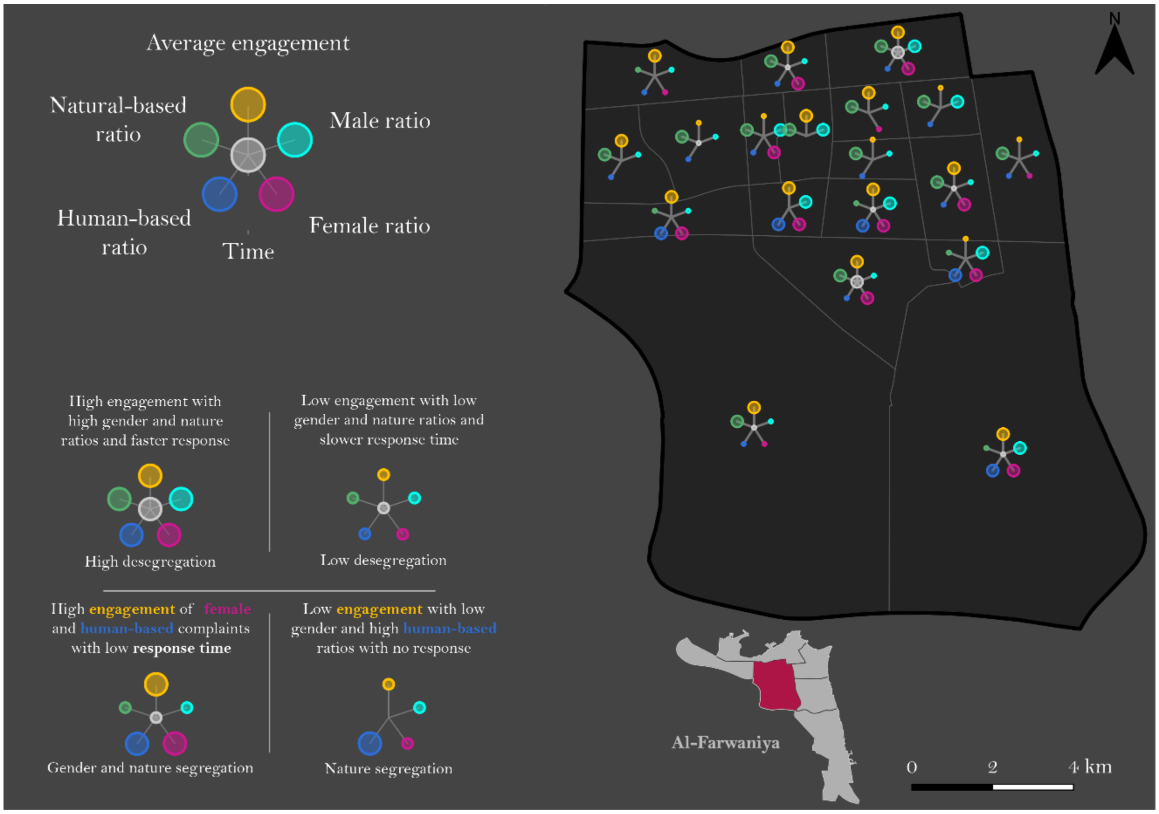


Figure 6.11. Multivariate map of citizen-government variables in Al-Farwaniya governorate.

Finally, the results of Mubarak Al-Kabeer governorate are illustrated in Figure 6.12. Like Hawalli and Al-Jahra (Figures 6.8 and 6.10 respectively), average engagement is balanced in this governorate, and no distinct cluster can be observed. There were balanced and high participation across gender, especially in the eastern areas. In some neighborhood-specific cases, however, male participation was predominant due to an absence of female participants. The nature of complaints was balanced overall, and it was noted that complaints based on incivilities were mostly located in the east. In contrast, natural-based complaints were high in western areas. Similar to Al-Farwaniya (Figure 6.11), responsiveness was low in most areas.

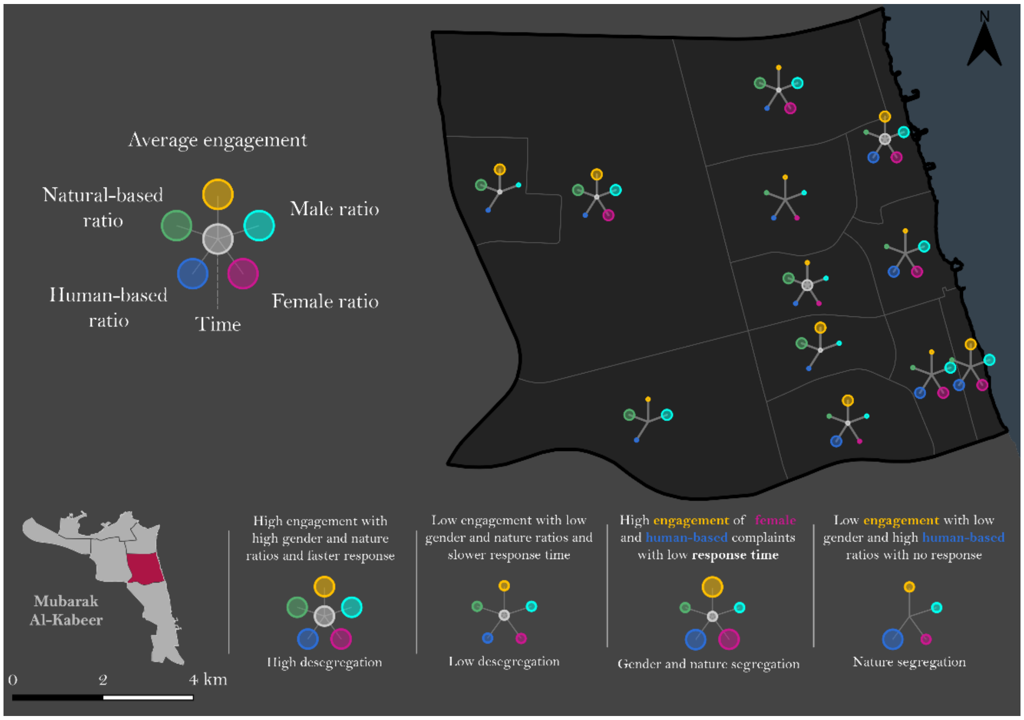


Figure 6.12. Multivariate map of citizen-government variables in Mubarak Al-Kabeer governorate.

Geovisualization of agency interconnectivity

As mentioned above, the data used for geovisualization of agency connectivity were captured at two spatial levels: (1) the country and (2) governorate level. Similar to the multivariate mapping section, the results of each governorate will be presented separately for better visual interpretation. For each geovisualization, a dashboard was created to include the case of Kuwait and governorate$_i$ for instant comparison. Recall that each dashboard included chord diagrams, adjacency matrix tables, and a map. The left panels represent the information at the country level, while the right panels represent the information at the governorate level. In the middle, a map of Kuwait with a highlighted governorate is included. To facilitate the process of recognizing agency names, Table 6.3

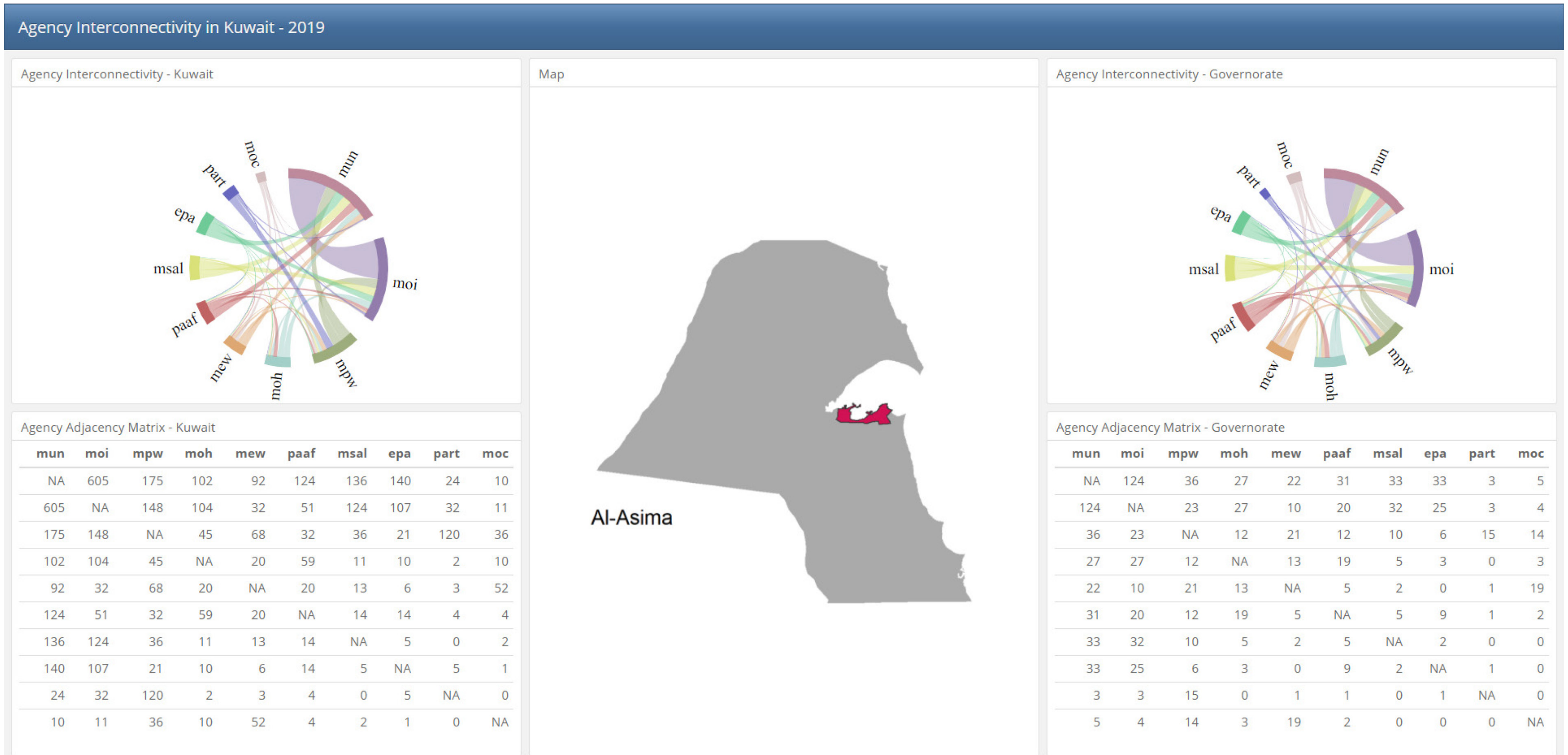
consists of both agency names and abbreviations. The abbreviation of the agency was used throughout this section.

Table 6.3. Agency name and abbreviation.

Name	Abbreviation
Municipality	MUN
Ministry of Interior	MOI
Ministry of Public Works	MPW
Ministry of Health	MOH
Ministry of Electricity and Water	MEW
Public Authority for Agricultural Affairs and Fish Resources	PAAF
Ministry of Social Affairs and Labor	MSAL
Environmental Public Authority	EPA
Public Authority for Roads and Transportation	PART
Ministry of Communications	MOC

The interconnectivity between the agencies of Al-Asima governorate is presented in Figure 6.13. Looking at Kuwait's connectivity results (left panel), the highest association was between mun and moi (605), and there were cases of no association among agencies including (msal/part) and (part/moc) in 2019. Several pairs have commonalities in their responsibilities that had high occurrences such as epa/mun and mpw/part. On the contrary, it was sensible to identify a low association between a pair of agencies with a contrast in their responsibilities such as epa/moc.

In Al-Asima, the highest pair of agencies was similar to the country's overall highest frequency pair (mun/moi) with 124 occurrences. There were six pairs of agencies where no associations exist (e.g., epa/moc and moh/part). Pairs with common responsibilities maintained their high occurrence in this governorate (e.g., epa/mun and part/mpw).



Agency Adjacency Matrix - Kuwait

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	605	175	102	92	124	136	140	24	10
605	NA	148	104	32	51	124	107	32	11
175	148	NA	45	68	32	36	21	120	36
102	104	45	NA	20	59	11	10	2	10
92	32	68	20	NA	20	13	6	3	52
124	51	32	59	20	NA	14	14	4	4
136	124	36	11	13	14	NA	5	0	2
140	107	21	10	6	14	5	NA	5	1
24	32	120	2	3	4	0	5	NA	0
10	11	36	10	52	4	2	1	0	NA

Agency Adjacency Matrix - Governorate

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	124	36	27	22	31	33	33	3	5
124	NA	23	27	10	20	32	25	3	4
36	23	NA	12	21	12	10	6	15	14
27	27	12	NA	13	19	5	3	0	3
22	10	21	13	NA	5	2	0	1	19
31	20	12	19	5	NA	5	9	1	2
33	32	10	5	2	5	NA	2	0	0
33	25	6	3	0	9	2	NA	1	0
3	3	15	0	1	1	0	1	NA	0
5	4	14	3	19	2	0	0	0	NA

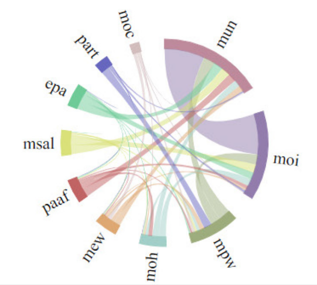
Figure 6.13. Al-Asima agency interconnectivity geovisualization dashboard.

The dashboard for the Hawalli governorate is illustrated in Figure 6.14. In Hawalli, the highest pair of agencies remained the same (mun/moi) with 120 occurrences. There were seven pairs of agencies where no association exists among them (e.g., part/moc and moh/part), which is more than Al-Asima governorate. This finding indicates that there is a spatial variation in the missing relationships among agencies. Pairs with common responsibilities maintained their high occurrence in this governorate (e.g., epa/mun and part/mpw). It was observed that msal was mostly associated with moi in this governorate, while the highest occurrence of msal in Kuwait and Al-Asima was with mun. This finding implies that agency associations have scale-dependent interrelationships (country and governorate).

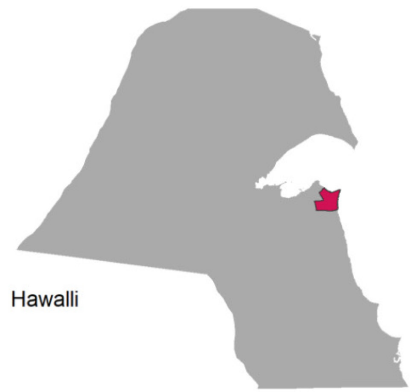
The results for the Al-Ahmadi governorate are presented in Figure 6.15. The pair mun/moi remained the highest associated agencies in this governorate with 124 occurrences. There were four cases of no association between agencies, which is less than previous governorates, and it extends the prior finding of varying nature of missing relationships in space. Similarly, agencies with common responsibilities had the highest associations, such as mpw/part. In Hawalli (Figure 6.14), mpw most occurrence was with mun, while in Al-Ahmadi, mpw occurred mostly with msal. This finding is an extension of the same results above regarding the varying nature of agency interrelationships from a spatial perspective.

Agency Interconnectivity in Kuwait - 2019

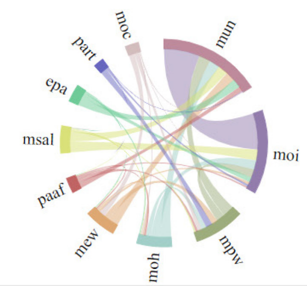
Agency Interconnectivity - Kuwait



Map



Agency Interconnectivity - Governorate



Agency Adjacency Matrix - Kuwait

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	605	175	102	92	124	136	140	24	10
605	NA	148	104	32	51	124	107	32	11
175	148	NA	45	68	32	36	21	120	36
102	104	45	NA	20	59	11	10	2	10
92	32	68	20	NA	20	13	6	3	52
124	51	32	59	20	NA	14	14	4	4
136	124	36	11	13	14	NA	5	0	2
140	107	21	10	6	14	5	NA	5	1
24	32	120	2	3	4	0	5	NA	0
10	11	36	10	52	4	2	1	0	NA

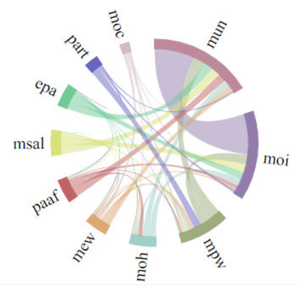
Agency Adjacency Matrix - Governorate

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	120	39	35	32	18	33	29	2	2
120	NA	28	31	9	5	36	16	7	1
39	28	NA	17	21	8	5	1	21	13
35	31	17	NA	5	7	3	3	0	5
32	9	21	5	NA	5	2	2	0	19
18	5	8	7	5	NA	1	1	1	0
33	36	5	3	2	1	NA	1	0	1
29	16	1	3	2	1	1	NA	0	0
2	7	21	0	0	1	0	0	NA	0
2	1	13	5	19	0	1	0	0	NA

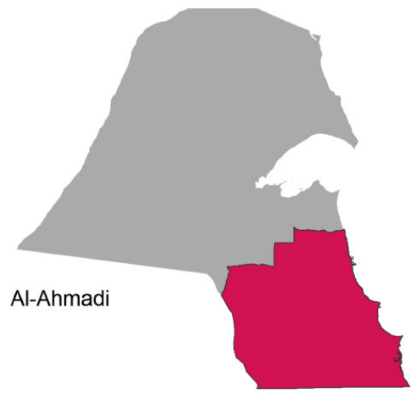
Figure 6.14. Hawalli agency interconnectivity geovisualization dashboard.

Agency Interconnectivity in Kuwait - 2019

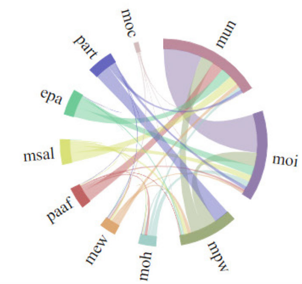
Agency Interconnectivity - Kuwait



Map



Agency Interconnectivity - Governorate



Agency Adjacency Matrix - Kuwait

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	605	175	102	92	124	136	140	24	10
605	NA	148	104	32	51	124	107	32	11
175	148	NA	45	68	32	36	21	120	36
102	104	45	NA	20	59	11	10	2	10
92	32	68	20	NA	20	13	6	3	52
124	51	32	59	20	NA	14	14	4	4
136	124	36	11	13	14	NA	5	0	2
140	107	21	10	6	14	5	NA	5	1
24	32	120	2	3	4	0	5	NA	0
10	11	36	10	52	4	2	1	0	NA

Agency Adjacency Matrix - Governorate

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	124	42	11	12	36	30	34	11	2
124	NA	44	19	6	7	20	30	11	2
42	44	NA	6	11	3	11	5	48	1
11	19	6	NA	1	8	2	1	1	1
12	6	11	1	NA	4	6	1	2	4
36	7	3	8	4	NA	2	0	1	1
30	20	11	2	6	2	NA	1	0	0
34	30	5	1	1	0	1	NA	1	1
11	11	48	1	2	1	0	1	NA	0
2	2	1	1	4	1	0	1	0	NA

Figure 6.15. Al-Ahmadi agency interconnectivity geovisualization dashboard.

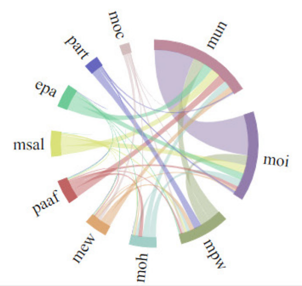
Figure 6.16 shows the visualizations for the Al-Jahra governorate. Similarly, mun/moi was the dominant pair in this governorate, with 77 occurrences. The number of pairs with no occurrence was higher compared to previous governorates with 11 pairs. This is an indication that the magnitude of the agency's interconnectivity is low. The agency with the least associations was moc, with six cases of no association. In extension to the varying association in space, moh occurred mostly with paaf while previously it occurred mostly with moi (in Al-Ahmadi) and mun (in Hawalli).

The results of the fifth governorate, Al-Farwaniya, are shown in Figure 6.17. Mun/moi remained the highest pair with 96 occurrences, which was higher than Al-Jahra (Figure 6.16). There were nine pairs with no associations among them, indicating a low agency’s interrelationship. The association between agencies with similar responsibilities remained the same (e.g., epa/mun and part/mpw).

Finally, the results for Mubarak Al-Kabeer are presented in Figure 6.18. With no change, mun/moi pair persisted the highest with 64 occurrences. Also, 15 pairs had no association among them. In other words, this governorate had the lowest agency interconnectivity in Kuwait. Previously, in Al-Farwaniya, moh was mostly associated with moi, while in Mubarak Al-Kabeer, moh occurred the most with mun. This observation is an additional support of the varying nature of agency association in space.

Agency Interconnectivity in Kuwait - 2019

Agency Interconnectivity - Kuwait

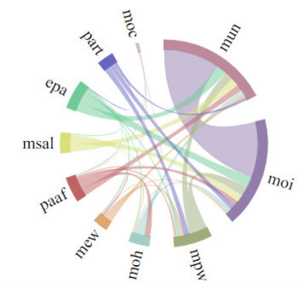


Agency Adjacency Matrix - Kuwait

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	605	175	102	92	124	136	140	24	10
605	NA	148	104	32	51	124	107	32	11
175	148	NA	45	68	32	36	21	120	36
102	104	45	NA	20	59	11	10	2	10
92	32	68	20	NA	20	13	6	3	52
124	51	32	59	20	NA	14	14	4	4
136	124	36	11	13	14	NA	5	0	2
140	107	21	10	6	14	5	NA	5	1
24	32	120	2	3	4	0	5	NA	0
10	11	36	10	52	4	2	1	0	NA

Map

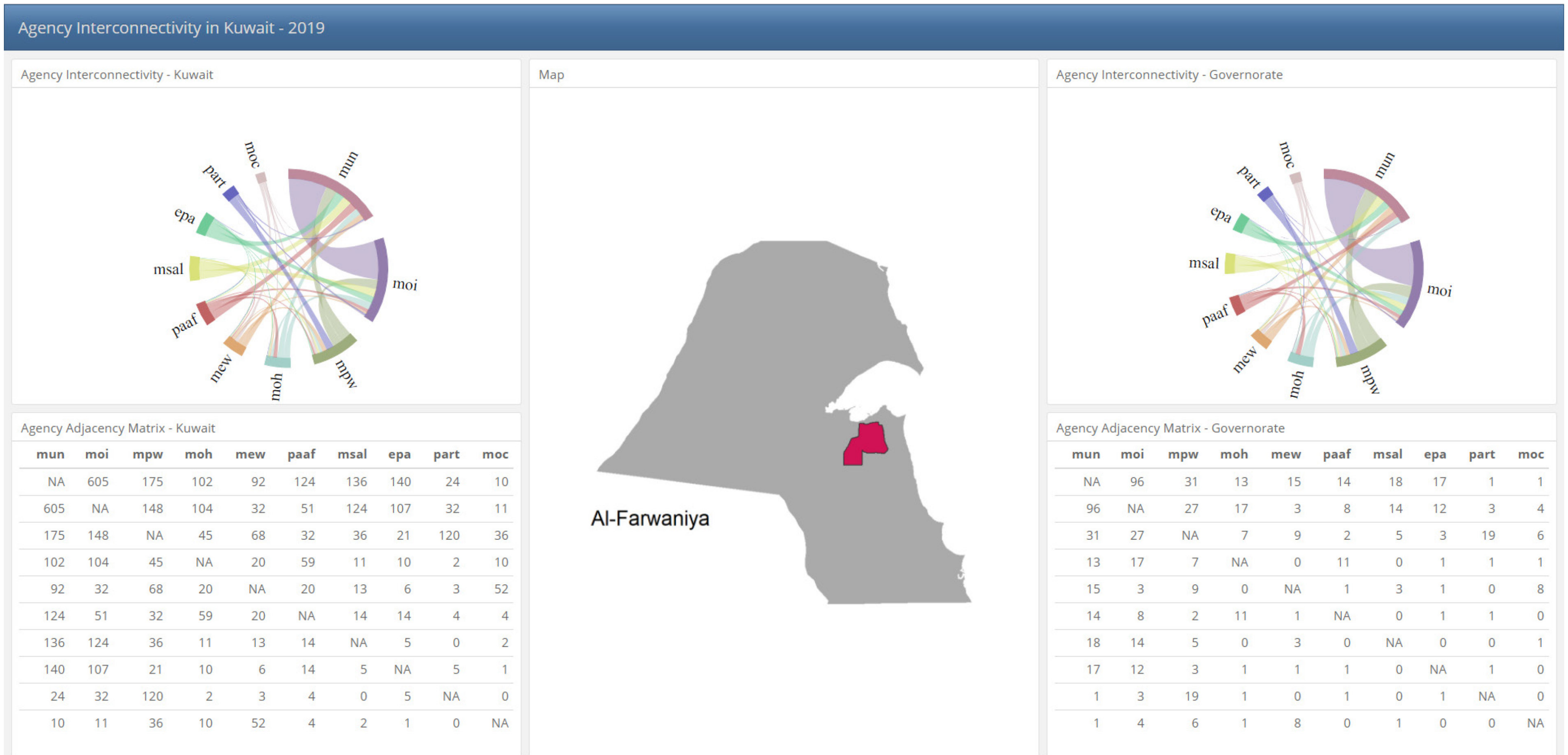
Agency Interconnectivity - Governorate



Agency Adjacency Matrix - Governorate

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	77	12	6	5	9	11	14	4	0
77	NA	13	6	3	7	10	14	7	0
12	13	NA	2	5	2	1	3	8	1
6	6	2	NA	1	8	1	1	0	0
5	3	5	1	NA	2	0	1	0	1
9	7	2	8	2	NA	1	1	0	1
11	10	1	1	0	1	NA	1	0	0
14	14	3	1	1	1	1	NA	1	0
4	7	8	0	0	0	0	1	NA	0
0	0	1	0	1	1	0	0	0	NA

Figure 6.16. Al-Jahra agency interconnectivity geovisualization dashboard.



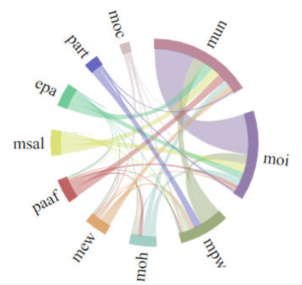
mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	605	175	102	92	124	136	140	24	10
605	NA	148	104	32	51	124	107	32	11
175	148	NA	45	68	32	36	21	120	36
102	104	45	NA	20	59	11	10	2	10
92	32	68	20	NA	20	13	6	3	52
124	51	32	59	20	NA	14	14	4	4
136	124	36	11	13	14	NA	5	0	2
140	107	21	10	6	14	5	NA	5	1
24	32	120	2	3	4	0	5	NA	0
10	11	36	10	52	4	2	1	0	NA

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	96	31	13	15	14	18	17	1	1
96	NA	27	17	3	8	14	12	3	4
31	27	NA	7	9	2	5	3	19	6
13	17	7	NA	0	11	0	1	1	1
15	3	9	0	NA	1	3	1	0	8
14	8	2	11	1	NA	0	1	1	0
18	14	5	0	3	0	NA	0	0	1
17	12	3	1	1	1	0	NA	1	0
1	3	19	1	0	1	0	1	NA	0
1	4	6	1	8	0	1	0	0	NA

Figure 6.17. Al-Farwaniya agency interconnectivity geovisualization dashboard.

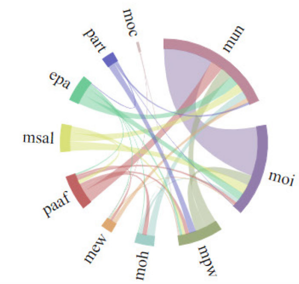
Agency Interconnectivity in Kuwait - 2019

Agency Interconnectivity - Kuwait



Map

Agency Interconnectivity - Governorate



Agency Adjacency Matrix - Kuwait

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	605	175	102	92	124	136	140	24	10
605	NA	148	104	32	51	124	107	32	11
175	148	NA	45	68	32	36	21	120	36
102	104	45	NA	20	59	11	10	2	10
92	32	68	20	NA	20	13	6	3	52
124	51	32	59	20	NA	14	14	4	4
136	124	36	11	13	14	NA	5	0	2
140	107	21	10	6	14	5	NA	5	1
24	32	120	2	3	4	0	5	NA	0
10	11	36	10	52	4	2	1	0	NA

Agency Adjacency Matrix - Governorate

mun	moi	mpw	moh	mew	paaf	msal	epa	part	moc
NA	64	15	10	6	16	11	13	3	0
64	NA	13	4	1	4	12	10	1	0
15	13	NA	1	1	5	4	3	9	1
10	4	1	NA	0	6	0	1	0	0
6	1	1	0	NA	3	0	1	0	1
16	4	5	6	3	NA	5	2	0	0
11	12	4	0	0	5	NA	0	0	0
13	10	3	1	1	2	0	NA	1	0
3	1	9	0	0	0	0	1	NA	0
0	0	1	0	1	0	0	0	0	NA

Figure 6.18. Mubarak l-Kabeer agency interconnectivity geovisualization dashboard.

Discussion

Bivariate mapping

Spatiotemporal bivariate mapping allowed for an investigation of gender disparities in making and engaging with citizen complaints in Kuwait. In a broad sense (Figure 6.4A), females participated in these activities more than men. One implication of this observation is that females might not be disproportionately affected by the digital divide in Kuwait (Ch. 5). However, this finding did not hold across time, as the balance of participation shifted toward males in certain seasons (Figure 6.4).

To the extent that geovisualization stimulates the development of research questions and hypotheses, the results from bivariate mapping suggest that a valuable avenue of research would involve collecting more precise data on social media users, by gender and socioeconomic status, across Kuwait, to determine whether higher female use is a reflection of the population of SM users in the country.

A second hypothesis to test would involve collecting data on territoriality motivations of SM users (e.g. O'Brien 2016a). One possible explanation for the patterns revealed in this chapter is possible that women in Kuwait possess a greater sense of *Territoriality* or place-ownership, giving them a greater predisposition toward reporting complaints at greater spatial extents (i.e., multiple neighborhoods beyond their home range).

Multivariate mapping

Multivariate maps that explored six relevant variables at the neighborhood level unlocked the possibilities of using geovisualization to enhance our understanding of citizen-government interactions. As concrete examples, areas in Al-Asima (Figure 6.7) were found to have high average engagement with complaint posts, and engagement was characterized by relatively low gender disparity. Areas in Hawalli (Figure 6.8) were shown to have more complaints about incivilities to which there were few documented governmental responses. In that sense, the geovisualization efforts document a consequential inequity that likely impacts local quality of life.

Against the backdrop of these opportunities, the chapter also experienced drawbacks of multivariate mapping. The level of complexity of such maps is high given the number of variables being mapped, requiring greater spatial and data literacy. Also, several symbol overlapping cases were causing visual clutter. Additionally, designing such maps require further mapping and software skills compared to simple univariate thematic maps. Nevertheless, with careful cartographic planning, design, and implementation, these drawbacks can be mitigated.

Geovisualization of agency interconnectivity

The results of the multiple geovisualization dashboards have shown several exciting findings. Both mun and moi had the highest pair association at the country and governorate level. This indicates that complaints involving both agencies might not be scale- or place-dependent. On the contrary, there were several cases where agencies had varying pairs depending on the location. For instance, moh had most occurrence with moi in Al-Farwaniya (Figure 6.17), while in Mubarak Al-Kabeer (Figure 6.18), moh was mostly associated with mun.

In addition, not all governorates had high pairs of affiliated agencies. In Mubarak Al-Kabeer, it was found that 15 pairs of agencies were not mentioned in any complaint.

This finding suggests that the magnitude of governmental connectivity varies at the governorate level. In Mubarak Al-Kabeer, the low level of interconnectivity implies that complaints are mostly associated with limited agencies. The highest level of pairs interconnectivity was found in Hawalli (Figure 6.14), implying a high level of interconnectivity.

The dynamic nature of agency interconnectivity may be due to variation in community demographics and the nature of complaints. Namely, building on the findings of the multivariate mapping section above, some areas had higher incivility complaints, which were mostly associated with more specific agencies (e.g., municipal waste and mun).

As a final point, note that "tagging" responsible agencies is not automated in the SM posts – it is a human action. Therefore, the appropriateness of agency tagging depends on the local knowledge of the citizen-reporter. This observation reflects a limitation of studying agency connectivity work, given that it is possible to link the wrong agency to a complaint mistakenly or based on a guess. As an example, one citizen wondered if the manhole in Figure 6.19 is under the responsibility of mpw, mew, or moc. Cases like these demonstrate the value of establishing a centralized system to coordinate complaints from citizens to the responsible agency. Government employees with specialized bureaucratic knowledge would presumably make these assignments more accurately than citizen volunteers.

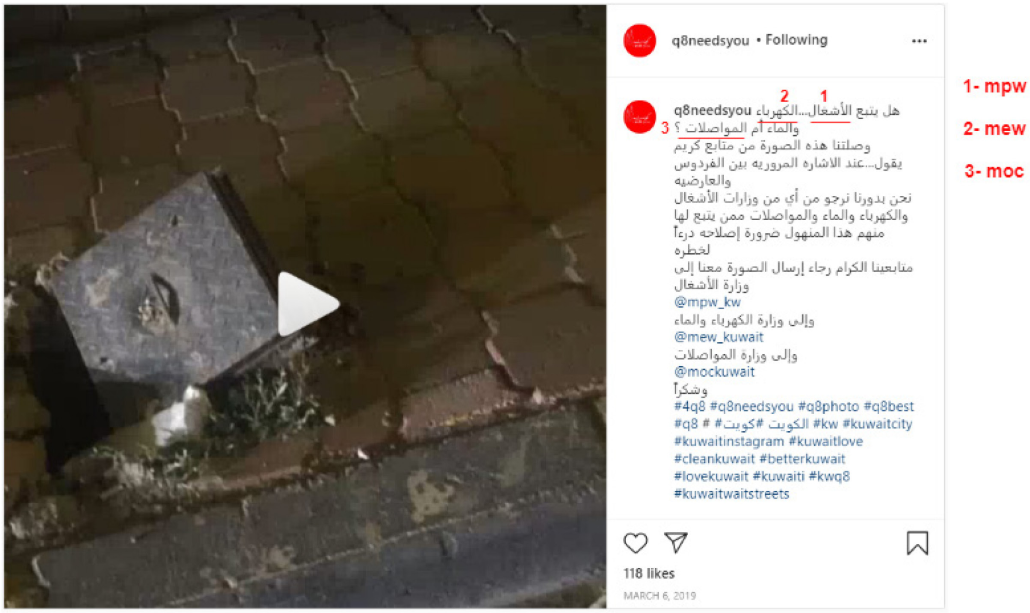


Figure 6.19. Example of a complaint with multiple associated agencies about a manhole based on citizen local knowledge.

Conclusion

In this chapter, advanced geovisualization methods were used to generate opportunities for exploring complex relationship in citizen-government interaction data in Kuwait. There were two main objectives in this chapter:

1. Implement multivariate mapping methods to identify spatiotemporal clusters of citizen-government interaction characteristics at the neighborhood level.
2. Implement geovisualization methods for agency interconnectivity at the country and governorate level.

Bivariate and multivariate mapping techniques were used to visualize multiple variables to identify any existence of spatiotemporal characteristics. Both methods facilitated the process of interpreting spatial patterns, despite the complexity level for creating the visualizations. Furthermore, the geovisual-dashboards revealed several findings regarding agency interconnectivity characteristics at the governorate level.

The findings of this research can be expanded by integrating authoritative data with the VGI data. In addition, including multi-temporal visualizations to explore changes in the complaint's characteristics in time should be considered. Using the same methodology established for objective 2, the analysis can be expanded to multi spatiotemporal scales to include interconnectivity at the neighborhood level and during each season.

7. CONCLUSION

Rapid urbanization and population growth increase the costs and complexity of providing “government goods” and services, and maintaining the urban commons, in cities and nations across the globe. Citizen involvement in this process—their co-production of the urban commons—lowers these costs for a local government. As such, many local governments are moving toward a centralized-point of communication for citizen-government interaction (e.g., the U.S. 311 system).

However, outside of most large urban areas, and particularly outside of the U.S. and other nations in the global North, such systems often do not exist. In the State of Kuwait, lack of such a system means that citizens must spend time and energy obtaining prior knowledge about responsible agencies and how to contact them prior to registering a complaint. With the rise of social media (SM) technologies, a group of volunteers, "Q8needsyou," began to close this gap by developing a 311-like system of communication, using SM, to receive citizen complaints and forward them to the appropriate governmental agency. Data from that project presents a novel research opportunity to understand the nature and spatialities of citizen complaints in Kuwait. Toward that end, this dissertation performed the following tasks:

i. Established a relational database design and structure for citizen complaints (Ch3).
ii. Revealed spatial clustering in complaint patterns (Ch4)

iii. Uncovered associations in patterns of complaints, demographic characteristics, and socioeconomic status that are consistent with studies of U.S.-based 311 systems (Ch5)

iv. Explored the nature of agency interconnectivity in Kuwait (Ch6).

The results of these efforts are promising. VGI-based complaints made to the volunteer-run SM account were shown to offer valuable data on citizen-government interactions in Kuwait. This observation is highly relevant for studying citizen complaints in study areas where obtaining authoritative data is complicated—either because such data do not exist (i.e., there is no 311 or 311-like system), because the data are siloed and incompatible (e.g., each agency keeps its own records using different methods and conventions), because the data are not shared by the appropriate government agency, or some combination of these reasons.

In addition to expanding the literature on citizen-government interactions out of formal 311 systems and into informal voluntary spaces, the dissertation extended scholarship on technology-based citizen-government co-production to a study area (Kuwait) that is outside of the U.S.-centric, global North context that dominates this stream of literature. Despite differences in both data sources and geographic, political, and institutional context, the results were remarkably consistent with 311 studies. Namely, the distribution of citizen complaints in Kuwait exhibits spatial clustering in ways that reflect underlying differences in citizen demographics and socioeconomic status.

Finally, while the findings revealed in this study contribute to academic scholarship, they also point to several public policy recommendations. This research relied only on VGI-based complaints. By implementing the database structure proposed in Chapter 3, it would be possible to augment governmental data with additional sources of citizen contributions (i.e., SM posts). Above all, to benefit from both sources, leveraging Kuwait's citizen-government interaction process requires establishing a centralized system that mimics the U.S. 311 system. With such a system, both authoritative and VGI-based complaints can converge, and citizens should find it easier to communicate with and participate in their government (Figure 7.1). Greater participation means greater co-production of a well-maintained, functional urban commons that invites deeper senses of co-ownership and place-based identity by citizens and the government alike.

Finally, the results of this dissertation rely heavily on the data source (i.e., VGI-based complaints). Despite the consistency with the literature, there are chances that these results may not hold true when using authoritative-based complaints. The former source was contributed by almost 2% of the population, which leaves a highly significant sample of the population not explored here. The size of the governmental agencies' complaints is known; thus, it would not be possible to speculate how the results would differ from using VGI-based data. With that in mind, the results are data-dependent, and this research should be extended in the future to include all complaint data sources.

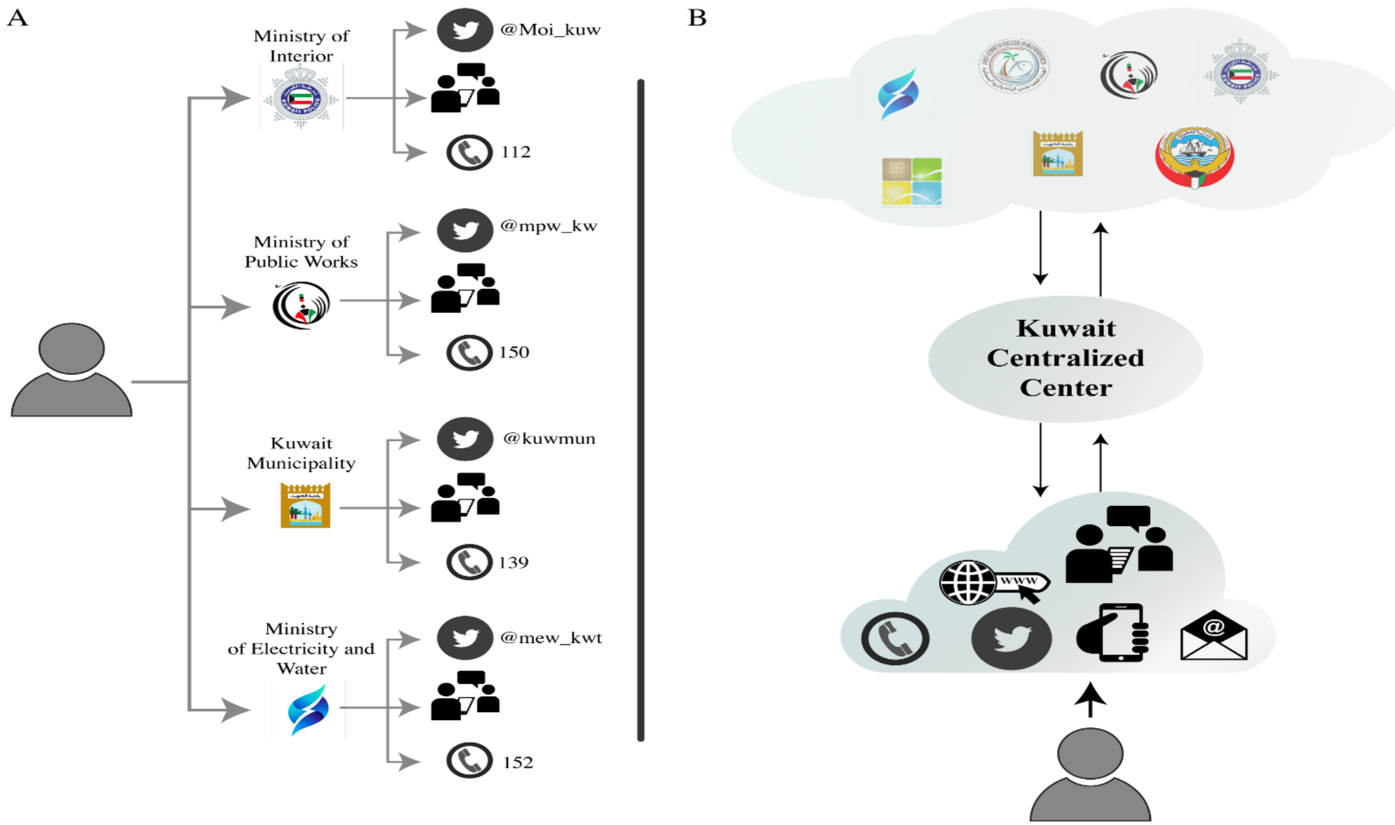


Figure 7.1. Proposed outline for a centralized system for non-emergency requests in Kuwait. In (A), the current scenario, citizens should obtain prior knowledge of whom and how to contact to submit a complaint. There could be multiple communication channels for each agency and thus increase the complexity of the communication experience. In (B), the proposed scenario, citizens communicate with the government through a single point of communication via multiple channels. Their complaints are received and re-directed to the responsible agency, relieving the citizen from the burden of guessing who should be responsible for his complaint. Once the complaint is resolved, the citizen is updated by the center. The agencies and channels of communications in this figure are for illustrative purposes.

REFERENCES

Alford, J. 2002. Why do public-sector clients coproduce? Toward a contingency theory. *Administration & Society* 34 (1):32–56.

Al-Nakib, F. 2016. *Kuwait transformed: a history of oil and urban life*. Stanford, California: Stanford University Press.

Alsahli, M. M., and M. Al-Harbi. 2018. Allocating optimum sites for air quality monitoring stations using GIS suitability analysis. *Urban Climate* 24:875–886.

Altman, I. 1970. Territorial behavior in humans: An analysis of the concept. *Spatial behavior of older people* :1–24.

Al-Yamani, F. Y., J. Bishop, E. Ramadhan, M. Al-Husaini, and A. N. Al-Ghadban. 2004. *Oceanographic atlas of Kuwait's waters*. Safat, Kuwait: Kuwait Institute for Scientific Research.

Attard, M., M. Haklay, and C. Capineri. 2016. The potential of volunteered geographic information (VGI) in future transport systems. *Urban Planning* 1 (4):6–19.

Aula, P. 2010. Social media, reputation risk and ambient publicity management. *Strategy & Leadership* 38 (6):43–49.

Bovaird, T. 2007. Beyond engagement and participation: User and community coproduction of public services. *Public administration review* 67 (5):846–860.

Brewer, G. A., B. J. Neubauer, and K. Geiselhart. 2006. Designing and Implementing E-Government Systems: Critical Implications for Public Administration and Democracy. *Administration & Society* 38 (4):472–499.

Brown, B. B. 1987. Territoriality. *Handbook of environmental psychology*.

Brown, B. B., and C. M. Werner. 1985. Social cohesiveness, territoriality, and holiday decorations: The influence of cul-de-sacs. *Environment and behavior* 17 (5):539–565.

Brown, G. 2009. Claiming a corner at work: Measuring employee territoriality in their workspaces. *Journal of environmental psychology* 29 (1):44–52.

Brown, G., and M. Kyttä. 2014. Key issues and research priorities for public participation GIS (PPGIS): A synthesis based on empirical research. *Applied Geography* 46:122–136.

Brudney, J. L., and R. E. England. 1983. Toward a definition of the coproduction concept. *Public administration review* :59–65.

Brudney, J. L., S. Fernandez, J. E. Ryu, and D. S. Wright. 2004. Exploring and explaining contracting out: Patterns among the American states. *Journal of Public Administration Research and Theory* 15 (3):393–419.

Campagna, M., R. Floris, P. Massa, A. Girsheva, and K. Ivanov. 2015. The role of social media geographic information (SMGI) in spatial planning. In *Planning support systems and smart cities*, 41–60. Springer.

Caughy, M. O., P. J. O'Campo, and J. Patterson. 2001. A brief observational measure for urban neighborhoods. *Health & place* 7 (3):225–236.

Cavallo, S., J. Lynch, and P. Scull. 2014. The digital divide in citizen-initiated government contacts: A GIS approach. *Journal of Urban Technology* 21 (4):77–93.

Central Statistical Bureau. 2011. Geoportal for Kuwait Census 2011. https://gis.csb.gov.kw/en/ (last accessed 27 September 2019).

———. 2020a. Central Statistical Bureau - Statistics of Transportation ch3. https://www.csb.gov.kw/Pages/Statistics_en?ID=41&ParentCatID=70 (last accessed 17 July 2020).

———. 2020b. General Statistics - Annual Statistical Abstract 2017/2018. https://www.csb.gov.kw/Pages/Statistics_en?ID=18&ParentCatID=2 (last accessed 9 October 2020).

———. 2020c. General Statistics - Annual Statistical Abstract in 25 Year 1990. https://www.csb.gov.kw/Pages/Statistics_en?ID=18&ParentCatID=2 (last accessed 10 October 2020).

———. 2020d. Population Statistics - Migration Statistics 2019. https://www.csb.gov.kw/Pages/Statistics_en?ID=56&ParentCatID=1 (last accessed 10 October 2020).

Chang, K.-T. 2018. *Introduction to geographic information systems* Ninth Edition. New York: McGraw-Hill Education.

Chen, I. J., and K. Popovich. 2003. Understanding customer relationship management (CRM) People, process and technology. *Business process management journal* 9 (5):672–688.

Chun, S., S. Shulman, R. Sandoval, and E. Hovy. 2010. Government 2.0: Making connections between citizens, data and government. *Information Polity* 15 (1, 2):1–9.

City of Chicago. 2019. Chicago History. https://www.chicago.gov/content/city/en/about/history.html (last accessed 28 July 2019).

Cordelia, A. 2007. E-government: towards the e-bureaucratic form? *Journal of information technology* 22 (3):265–274.

Corea, F. 2016. *Big data analytics: A management perspective*. Springer.

———. 2019. Introduction to Data. In *An Introduction to Data*, 1–5. Cham: Springer International Publishing http://link.springer.com/10.1007/978-3-030-04468-8_1 (last accessed 28 July 2019).

Cox, K. R. 2017. Spaces of dependence, spaces of engagement and the politics of scale, or: looking for local politics. In *Politics*, 257–280. Routledge.

Craglia, M., F. Ostermann, and L. Spinsanti. 2012. Digital Earth from vision to practice: making sense of citizen-generated content. *International Journal of Digital Earth* 5 (5):398–416.

Criado, J. I., R. Sandoval-Almazan, and J. R. Gil-Garcia. 2013. *Government innovation through social media*. Elsevier.

Crutcher, M., and M. Zook. 2009. Placemarks and waterlines: Racialized cyberscapes in post-Katrina Google Earth. *Geoforum* 40 (4):523–534.

Dave Chaffey. 2019. Global social media research summary 2019. *Smart Insights*. https://www.smartinsights.com/social-media-marketing/social-media-strategy/new-global-social-media-research/ (last accessed 31 July 2019).

De Mauro, A., M. Greco, and M. Grimaldi. 2015. What is big data? A consensual definition and a review of key research topics. In *AIP conference proceedings*, 97–104. AIP.

Dent, B. D., J. S. Torguson, and T. W. Hodler. 2009. *Cartography: thematic map design* 6th ed. New York: McGraw-Hill Higher Education.

Dovey, T., and W. Eggers. 2008. *National issues dialogues Web 2.0: The future of collaborative government*. Washington, DC: Deloitte Research.

Dumbill, E. 2013. *Making sense of big data*. Mary Ann Liebert, Inc. 140 Huguenot Street, 3rd Floor New Rochelle, NY 10801 USA.

Dykes, J., A. M. MacEachren, and M.-J. Kraak. 2005. *Exploring geovisualization*. Amsterdam: Elsevier. http://public.eblib.com/choice/publicfullrecord.aspx?p=344649 (last accessed 22 September 2020).

Edney, J. J. 1974. Human territoriality. *Psychological Bulletin* 81 (12):959.

Elwood, S. 2008. Volunteered geographic information: key questions, concepts and methods to guide emerging research and practice. *GeoJournal* 72 (3–4):133–135.

———. 2009. Geographic Information Science: new geovisualization technologies — emerging questions and linkages with GIScience research. *Progress in Human Geography* 33 (2):256–263.

Elwood, S., M. F. Goodchild, and D. Z. Sui. 2012. Researching volunteered geographic information: Spatial data, geographic research, and new social practice. *Annals of the association of American geographers* 102 (3):571–590.

Engler, M., and P. Engler. 2017. *This is an uprising: how nonviolent revolt is shaping the twenty-first century*. New York: Nation Books.

Engler, N. J., T. Scassa, and D. F. Taylor. 2014. Cybercartography and volunteered geographic information. In *Modern Cartography Series*, 43–57. Elsevier.

Environmental Public Authority. 2020. Beatona - Explore Our Environment. https://enterprise.emisk.org/eMISKExploreOurEnvironment/?bgLayer=OSM&lang=en.

Eshleman, R., and H. Yang. 2014. " Hey# 311, Come Clean My Street!": A Spatio-temporal Sentiment Analysis of Twitter Data and 311 Civil Complaints. In *2014 IEEE Fourth International Conference on Big Data and Cloud Computing*, 477–484. IEEE.

ESRI. 2020a. How Average Nearest Neighbor works—ArcGIS Pro | Documentation. https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-average-nearest-neighbor-distance-spatial-st.htm (last accessed 26 June 2020).

———. 2020b. How Multi-Distance Spatial Cluster Analysis (Ripley's K-function) works—ArcGIS Pro | Documentation. https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-multi-distance-spatial-cluster-analysis-ripl.htm (last accessed 26 June 2020).

Field, K. 2018. *Cartography: a compendium of design thinking for mapmakers*. Redlands, California: Esri Press.

Fischel, W. A. 2001. Homevoters, municipal corporate governance, and the benefit view of the property tax. *National Tax Journal* :157–173.

Flanagin, A. J., and M. J. Metzger. 2008. The credibility of volunteered geographic information. *GeoJournal* 72 (3–4):137–148.

Fleming, C. 2008. Customer service and 311/CRM technology in local governments: Lessons on connecting with citizens. ICMA.

Fleming, C., and B. Barnhouse. 2006. Call 311: Connecting citizens to local government case study series. *San Antonio Customer Service* 311.

Flora, C. B., J. L. Flora, and S. P. Gasteyer. 2016. *Rural communities: legacy and change* Fifth edition. Boulder, CO: Westview Press.

Ganapati, S. 2010. *Using geographic information systems to increase citizen engagement*. Washington, DC: IBM Center for the Business of Government.

———. 2011. Uses of Public Participation Geographic Information Systems Applications in E-Government. *Public Administration Review* 71 (3):425–434.

Gao, X. 2018. Networked co-production of 311 services: Investigating the use of Twitter in five US cities. *International Journal of Public Administration* 41 (9):712–724.

Goldfarb, A., and J. Prince. 2008. Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics and Policy* 20 (1):2–15.

Goodchild, M. F. 2007. Citizens as sensors: the world of volunteered geography. *GeoJournal* 69 (4):211–221.

Gouveia, C., and A. Fonseca. 2008. New approaches to environmental monitoring: the use of ICT to explore volunteered geographic information. *GeoJournal* 72 (3–4):185–197.

Grekousis, G. 2020. *Spatial analysis methods and practice: describe - explore - explain through GIS* First edition. New York, NY: Cambridge University Press.

Grover, A. 2015. Evaluating the Portability of Health Care Data to SQL Like Big Data Environment.

Guan, X., and C. Chen. 2014. Using social media data to understand and assess disasters. *Natural Hazards* 74 (2):837–850.

Harris, P. B., and B. B. Brown. 1996. The home and identity display: Interpreting resident territoriality from home exteriors. *Journal of Environmental Psychology* 16 (3):187–203.

Hartmann, S., A. Mainka, and W. G. Stock. 2017. Citizen relationship management in local governments: The potential of 311 for public service delivery. In *Beyond Bureaucracy*, 337–353. Springer.

Haworth, B., and E. Bruce. 2015. A review of volunteered geographic information for disaster management. *Geography Compass* 9 (5):237–250.

Hiles, A. N. 1994. Service level agreements: Panacea or pain? *The TQM Magazine* 6 (2):14–16.

Himelboim, I., M. Smith, and B. Shneiderman. 2013. Tweeting apart: Applying network analysis to detect selective exposure clusters in Twitter. *Communication methods and measures* 7 (3–4):195–223.

Holmes, S. T. 2007. Building a 311 system: A case study of the Orange County, Florida, government service center. *US Department of Justice, Office of Community Oriented Policing Services*.

Holzer, M., R. Schwester, A. McGuire, and K. Kloby. 2006. State-level 311 systems: leveraging service enhancement and performance measurement at the state level. *The Book of the States* 38:409–413.

Houston, J. B., J. Hawthorne, M. F. Perreault, E. H. Park, M. Goldstein Hode, M. R. Halliwell, S. E. Turner McGowen, R. Davis, S. Vaid, and J. A. McElderry. 2015. Social media and disasters: a functional framework for social media use in disaster planning, response, and research. *Disasters* 39 (1):1–22.

Huang, Q., and D. W. Wong. 2016. Activity patterns, socioeconomic status and urban spatial structure: what can social media data tell us? *International Journal of Geographical Information Science* 30 (9):1873–1898.

IBM. 2018. The Four V's of Big Data. *IBM Big Data & Analytics Hub*. https://www.ibmbigdatahub.com/infographic/four-vs-big-data (last accessed 5 August 2019).

Ibrahim, R., and M. O. Shafiq. 2017. Measurement and analysis of citizens requests to government for non-emergency services. In *2017 Twelfth International Conference on Digital Information Management (ICDIM)*, 286–291. IEEE.

Idicheria, C. E., A. Schellong, J. Fiedler, M. Kammer, M.-T. Huppertz, and H. Westerfeld. 2012. *A Review of 311 in New York City*. Technical report. Interdisziplinäre Studien zu Politik, Recht ….

Irani, Z., M. Al-Sebie, and T. Elliman. 2006. Transaction stage of e-government systems: identification of its location and importance. In *Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06)*, 82c–82c. IEEE.

Jakobsen, M., and S. C. Andersen. 2013. Coproduction and equity in public service delivery. *Public Administration Review* 73 (5):704–713.

Johnson, P. A., and R. E. Sieber. 2013. Situating the adoption of VGI by government. In *Crowdsourcing geographic knowledge*, 65–81. Springer.

Kavanagh, S. C. 2007. An introduction to CRM. *Revolutionizing Constituent Relationships: The Promise of CRM Systems for the Public Sector* :9–19.

Kim, G.-H., S. Trimi, and J.-H. Chung. 2014. Big-data applications in the government sector. *Communications of the ACM* 57 (3):78–85.

King, C. S., and R. Nank. 2011. The context: Citizens, administrators, and their discontents. In *Government is Us 2.0*, 17–30. Routledge.

King, S. F. 2007. Citizens as customers: Exploring the future of CRM in UK local government. *Government Information Quarterly* 24 (1):47–63.

Kirk, A. 2016. *Data visualisation: a handbook for data driven design*. Los Angeles: SAGE.

Kontokosta, C., B. Hong, and K. Korsberg. 2017. Equity in 311 Reporting: Understanding Socio-Spatial Differentials in the Propensity to Complain. *arXiv:1710.02452 [cs]*. http://arxiv.org/abs/1710.02452 (last accessed 28 March 2019).

Kryvasheyeu, Y., H. Chen, N. Obradovich, E. Moro, P. Van Hentenryck, J. Fowler, and M. Cebrian. 2016. Rapid assessment of disaster damage using social media activity. *Science advances* 2 (3):e1500779.

Kuk, G. 2003. The digital divide and the quality of electronic service delivery in local government in the United Kingdom. *Government Information Quarterly* 20 (4):353–363.

Kuwait Finance House. 2020. Economic Reports - Real Estate Reports. https://www.kfh.com/en/home/Investor-Relations/Economic-reports/Economic-reports.html (last accessed 10 October 2020).

Kuwait Municipality. 2013. Kuwait Municipality - Directory of Master Planning. http://ud.baladia.gov.kw/main-web/masterplan/new/current.htm#.X4B3f9AzaUk (last accessed 9 October 2020).

Laney, D. 2001. 3D data management: Controlling data volume, velocity and variety. *META group research note* 6 (70):1.

Lienhardt, P. 1993. *Disorientations: A society in flux: Kuwait in the 1950s*. Ithaca.

Lin, W. 2013. When Web 2.0 Meets Public Participation GIS (PPGIS): VGI and Spaces of Participatory Mapping in China. In *Crowdsourcing Geographic Knowledge*, eds. D. Sui, S. Elwood, and M. Goodchild, 83–103. Dordrecht: Springer Netherlands http://www.springerlink.com/index/10.1007/978-94-007-4587-2_6 (last accessed 5 August 2019).

Linders, D. 2012. From e-government to we-government: Defining a typology for citizen coproduction in the age of social media. *Government Information Quarterly* 29 (4):446–454.

Loeffler, E., and T. Bovaird. 2016. User and community co-production of public services: What does the evidence tell us? *International Journal of Public Administration* 39 (13):1006–1019.

Lovejoy, K., and G. D. Saxton. 2012. Information, community, and action: How nonprofit organizations use social media. *Journal of computer-mediated communication* 17 (3):337–353.

Lu, Q., and P. A. Johnson. 2016. Characterizing new channels of communication: A case study of municipal 311 requests in Edmonton, Canada. *Urban Planning* 1 (2):18–31.

Luc Anselin. 2019. Local Spatial Autocorrelation (1). https://geodacenter.github.io/workbook/6a_local_auto/lab6a.html (last accessed 26 June 2020).

Malleson, N., and M. A. Andresen. 2015. The impact of using social media data in crime rate calculations: shifting hot spots and changing spatial patterns. *Cartography and Geographic Information Science* 42 (2):112–121.

Marin, A., and B. Wellman. 2011. Social network analysis: An introduction. *The SAGE handbook of social network analysis* 11.

Marr, B. 2015. *Big Data: Using SMART big data, analytics and metrics to make better decisions and improve performance*. John Wiley & Sons.

McAfee, A., E. Brynjolfsson, T. H. Davenport, D. J. Patil, and D. Barton. 2012. Big data: the management revolution. *Harvard business review* 90 (10):60–68.

McCall, M. K. 2003. Seeking good governance in participatory-GIS: a review of processes and governance dimensions in applying GIS to participatory spatial planning. *Habitat International* 27 (4):549–573.

McCall, M. K., and C. E. Dunn. 2012. Geo-information tools for participatory spatial planning: Fulfilling the criteria for ‘good’ governance? *Geoforum* 43 (1):81–94.

Minkoff, S. L. 2016. NYC 311: A Tract-Level Analysis of Citizen–Government Contacting in New York City. *Urban Affairs Review* 52 (2):211–246.

Minoprio, A., H. Spencely, and P. W. MacFarlane. 1953. Town planning in Kuwait. *Architectural Design* :272–81.

Morabito, V. 2015. Big data and analytics. *Strategic and organisational impacts*.

Nah, S., and G. D. Saxton. 2013. Modeling the adoption and use of social media by nonprofit organizations. *New media & society* 15 (2):294–313.

Nam, T., and T. A. Pardo. 2014. Understanding Municipal Service Integration: An Exploratory Study of 311 Contact Centers. *Journal of Urban Technology* 21 (1):57–78.

NapoleonCat. 2020. Instagram users in Kuwait - December 2019. https://napoleoncat.com/stats/instagram-users-in-kuwait/2019/12 (last accessed 27 September 2020).

Nelson, J. 2020. Multivariate Mapping. The Geographic Information Science & Technology Body of Knowledge (1st Quarter 2020 Edition). *John P. Wilson (ed.)*. https://gistbok.ucgis.org/bok-topics/multivariate-mapping.

Nossov, L., H. Ernst, and V. Chupis. 2016. Practical Experience with Formal SQL Tuning. In *Formal SQL Tuning for Oracle Databases*, 79–92. Berlin, Heidelberg:

Springer Berlin Heidelberg http://link.springer.com/10.1007/978-3-662-50417-8_7 (last accessed 5 August 2019).

O'Brien, D. T. 2013. Custodians and custodianship in urban neighborhoods: A methodology using reports of public issues received by a city's 311 hotline. *Environment and Behavior* 47 (3):304–327.

O'Brien, D. T. 2016a. 311 hotlines, territoriality, and the collaborative maintenance of the urban commons: Examining the intersection of a coproduction policy and evolved human behavior. *Evolutionary Behavioral Sciences* 10 (2):123.

———. 2016b. Using small data to interpret big data: 311 reports as individual contributions to informal social control in urban neighborhoods. *Social Science Research* 59:83–96.

Ostrom, E. 1996. Crossing the great divide: coproduction, synergy, and development. *World development* 24 (6):1073–1087.

Parks, R. B., P. C. Baker, L. Kiser, R. Oakerson, E. Ostrom, V. Ostrom, S. L. Percy, M. B. Vandivort, G. P. Whitaker, and R. Wilson. 1981. Consumers as coproducers of public services: Some economic and institutional considerations. *Policy Studies Journal* 9 (7):1001–1011.

Paulin, A. 2013. Towards Self-Service Government-A Study on the Computability of Legal Eligibilities. *J. UCS* 19 (12):1761–1791.

Pestoff, V., S. P. Osborne, and T. Brandsen. 2006. Patterns of co-production in public services: Some concluding thoughts. *Public Management Review* 8 (4):591–595.

Public Authority for Civil Information. 2019. Statistics Services System - Historical Data. https://www.paci.gov.kw/stat/TimeSeries.aspx (last accessed 29 April 2019).

Reddick, C. G. 2010. Impact of citizen relationship management (CRM) on government: Evidence from US local governments. *Journal of E-governance* 33 (2):88–99.

Revelle, W. 2020. *psychTools: Tools to Accompany the "psych" Package for Psychological Research*. https://CRAN.R-project.org/package=psychTools (last accessed 29 July 2020).

Richter, P., J. Cornford, and I. McLoughlin. 2004. The e-Citizen as talk, as text and as technology: CRM and e-Government. *Electronic Journal of e-government* 2 (3):207–218.

Robinson, A. H., J. L. Morrison, P. C. Muehrcke, A. J. Kimerling, and S. C. Guptill eds. 1995. *Elements of cartography* 6th ed. New York: Wiley.

Rogerson, P. 2019. *Statistical methods for geography* 5th ed. LA: SAGE.

Rouse, L. J., S. J. Bergeron, and T. M. Harris. 2007. Participating in the Geospatial Web: Collaborative Mapping, Social Networks and Participatory GIS. In *The Geospatial Web*, eds. A. Scharl and K. Tochtermann, 153–158. London: Springer London http://link.springer.com/10.1007/978-1-84628-827-2_14 (last accessed 5 August 2019).

Sæbø, Ø., J. Rose, and L. Skiftenes Flak. 2008. The shape of eParticipation: Characterizing an emerging research area. *Government Information Quarterly* 25 (3):400–428.

Schellong, A. 2008. *Citizen Relationship Management: A Study of CRM in Government*. Frankfurt, Germany: Peter Lang.

Schellong, A., and T. Langenberg. 2007. Managing citizen relationships in disasters: Hurricane wilma, 311 and miami-dade county. In *2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07)*, 96–96. IEEE.

Schwester, R. W., T. Carrizales, and M. Holzer. 2009. An examination of the municipal 311 system. *International Journal of Organization Theory & Behavior* 12 (2):218–236.

Scopus. 2019. Document search. https://www-scopus-com.libproxy.txstate.edu/search/form.uri?display=basic (last accessed 29 July 2019).

Sieber, R. 2006. Public Participation Geographic Information Systems: A Literature Review and Framework. *Annals of the Association of American Geographers* 96 (3):491–507.

Simon Kemp. 2019. Digital 2019: Kuwait. *DataReportal – Global Digital Insights*. https://datareportal.com/reports/digital-2019-kuwait (last accessed 24 September 2020).

Singleton, A. D., S. Spielman, and D. Folch. 2017. *Urban analytics*. Sage Publications.

Slocum, T. A., R. B. McMaster, F. Kessler C., and H. H. Howard eds. 2009. *Thematic cartography and geovisualization* 3rd ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Smith, N. 2012. Homeless/global: Scaling places. In *Mapping the futures*, 102–135. Routledge.

Stehman, S. V., C. C. Fonte, G. M. Foody, and L. See. 2018. Using volunteered geographic information (VGI) in design-based statistical inference for area estimation and accuracy assessment of land cover. *Remote Sensing of Environment* 212:47–59.

Stephens, M. 2013. Gender and the GeoWeb: divisions in the production of user-generated cartographic information. *GeoJournal* 78 (6):981–996.

Stevens, J. 2015. Bivariate Choropleth Maps: A How-to Guide. https://www.joshuastevens.net/cartography/make-a-bivariate-choropleth-map/ (last accessed 22 September 2020).

Swyngedouw, E. 2004. Globalisation or 'glocalisation'? Networks, territories and rescaling. *Cambridge Review of International Affairs* 17 (1):25–48.

Taylor, R. B. 1988. *Human territorial functioning: An empirical, evolutionary perspective on individual and small group territorial cognitions, behaviors, and consequences*. Cambridge University Press.

Teo, T. S., P. Devadoss, and S. L. Pan. 2006. Towards a holistic perspective of customer relationship management (CRM) implementation: A case study of the Housing and Development Board, Singapore. *Decision support systems* 42 (3):1613–1627.

Torres, L. H. 2007. Citizen sourcing in the public interest. *Knowledge Management for Development Journal* 3 (1):134–145.

Tulloch, D. L. 2008. Is VGI participation? From vernal pools to video games. *GeoJournal* 72 (3–4):161–171.

Tumin, Z., and R. Wasserman. 2008. Nine Imperatives For Leadership of 311-Enabled Government. *The report of the* 311:15–16.

United Nations, Department of Economic and Social Affairs, Population Division. 2015. *World Population Prospects: The 2015 Revision, Key Findings and Advance Tables*. New York.

Verplanke, J., M. K. McCall, C. Uberhuaga, G. Rambaldi, and M. Haklay. 2016. A shared perspective for PGIS and VGI. *The Cartographic Journal* 53 (4):308–317.

Wang, L., C. Qian, P. Kats, C. Kontokosta, and S. Sobolevsky. 2017. Structure of 311 service requests as a signature of urban location ed. Y. Chen. *PLOS ONE* 12 (10):21.

Weaver, R. 2019. Erasing Red Lines: Part 3-Building Community Wealth. *Cornell University*. https://ecommons.cornell.edu/handle/1813/73617.

Weaver, R., S. Bagchi-Sen, J. Knight, and A. E. Frazier. 2016. *Shrinking cities: Understanding urban decline in the United States*. Routledge.

Werner, C. M., S. Peterson-Lewis, and B. B. Brown. 1989. Inferences about homeowners' sociability: Impact of Christmas decorations and other cues. *Journal of Environmental Psychology* 9 (4):279–296.

Whitaker, G. P. 1980. Coproduction: Citizen participation in service delivery. *Public administration review* :240–246.

Wimmer, M. A., and E. Tambouris. 2002. Online one-stop government. In *IFIP World Computer Congress, TC 8*, 117–130. Springer.

Wright, E. O., and J. Rogers. 2015. *American society: how it really works* Second edition. New York: W.W. Norton & Company.

Xu, L., M.-P. Kwan, S. McLafferty, and S. Wang. 2017. Predicting demand for 311 non-emergency municipal services: An adaptive space-time kernel approach. *Applied Geography* 89:133–141.

Zobel, C. W., M. Baghersad, and Y. Zhang. 2017. Calling 311: evaluating the performance of municipal services after disasters. In *14th int. ISCRAM conf.*, 164–172.