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Research Article

Smart city re-imagined: City planning and GeoAI in the age of big data

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ABSTRACT

This paper aims to engage with the ongoing debates on the role of planning in future smart cities, to make a case for a reconceptualization of the technocentric notion of the smart city, and to elevate the position of city planning within the smart-city discourse. The central argument made is that the smart city could exploit the synergies between city planning and three techno-scientific domains including Big Data, Geographic Information Science and Systems, and Data Science—-which collectively constitute an emerging field known as Geospatial Artificial Intelligence (Geo-AI)— to meet four overarching policy goals: 1) to enhance the efficiency of urban services and functions; 2) to improve quality of life for all urban citizens; 3) to address the pressing societal, ecological and economic challenges that could plague urban systems on different levels; and, 4) to contribute to the production of spatial data, information and knowledge on human-urban dynamics. In addition, the paper defines a human-centered conceptual framework illustrating how the cross-pollination between city planning and the three techno-scientific fields could enhance the planning practice and accomplish the smart-city policy goals. The methodology employed in this study entails a systematic review of the literature. In addition to discussing the latest achievements as well as the progress made on the nexus of city planning and GeoAI, the paper also highlights the barriers to the application of GeoAI in the planning, design and management of smart cities and identifies potential avenues for future research.

1. Introduction

Over the past decade, as a result of the exponential growth of urban big data, as well as rapid advances in geospatial technologies, information and communications technologies (ICTs) and computational power, the notion of the smart city has gained traction in political, industrial, governmental, and academic domains. In fact, the smart city, which first emerged in North America in the context of smart growth— itself a planning movement aimed at protecting natural resources and curbing urban sprawl— has been viewed, quite optimistically, as a universal solution to all the acute crises surrounding cities (Geertman et al., 2015; Yigitcanlar et al., 2018). Yet there is no consensus in the literature around the definition of the smart city. Further, most recent conceptualizations of the smart city place networked computing and digitally embedded gadgets and technologies (collectively termed “everyware” by Greenfield (2006)), as well as the potential economic growth driven by sociotechnical innovation (Kim et al., 2021) at the center of their proposed framings. For instance, according to Li et al. (2020), this concept refers to a city that utilizes “digital technology in the interests of improving its

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operations and management, and addressing the problems that afflict the modern city." The increased application of the smart-city agenda, programs and initiatives across the globe has triggered academic debates on the new modes of urban governance (Bayat & Kawalek, 2021; Kitchin et al., 2019b), the fierce competition among cities to maintain their innovation edge in the emerging knowledge-based economy (Hollands, 2015), and the challenges associated with the privatization and corporatization of urban infrastructure and services (Carr & Hesse, 2020; Karvonen et al., 2019).

In this paper, we aim to rethink the techno-centric notion of the smart city and to elevate the position of city planning (encompassing urban design, urban planning and urban management subfields) within the smart-city discourse. We are mindful of the major critiques, challenges, and risks associated with the smart city (in terms of reproduction of an unequitable form of political economy and of wider unintended consequences of the application of smart-city technologies with respect to the fundamental human rights, such as equity, citizenship, democracy, governance, privacy, ethics, inclusiveness, and civil liberty — among others) (See Haque, 2012; Kitchin, 2014a; Kitchin et al., 2017, 2019a). Therefore, our work intends to contribute to the growing body of scholarship that strives to bridge the gap between critics and proponents of the smart city and to offer pragmatic solutions to mitigate the deficiencies of smart city agenda (Degbelo et al., 2016; Jiang et al., 2020; Kitchin, 2021; Sadowski, 2019). It also aims to engage with and extend the recent academic debates around the role of urban planning in future smart cities (Cowley & Caprotti, 2019; Karvonen et al., 2020; Morgan & Webb, 2020), as well as the need to bridge the gaps between smart-city initiatives and sustainability goals (Evans et al., 2019). Through conceptual analyses and empirical examples, we demonstrate that the smart city could exploit the synergies between city planning and three techno-scientific domains including Big Data, Geographic Information Science and Systems, and Data Science—which collectively constitute an emerging field known as Geospatial Artificial Intelligence (GeoAI)— to meet four overarching smart-city goals.

The methodology employed in this study entails a systematic review of the literature, focusing mainly on the potential areas of collaboration and cross-fertilization between smart cities, city planning, and GeoAI. The main underlying question that guides this paper is how the planning discipline, both in theory and in practice, could leverage GeoAI to better understand, analyze, and visualize the ways in which people use, experience, perceive, and navigate urban spaces; to enhance collaboration and public engagement efforts in the planning, design and management of cities; to better inform land use, transportation and environmental policies; and to help create healthy, sustainable, connected, equitable, and resilient places and communities.

The remainder of this paper is organized as follows: Section 2 briefly sheds light on the digital infrastructure of smart cities and illustrates how this digital framework interfaces with the technological underpinnings of GeoAI, stressing the capabilities of GeoAI in addressing smart-city problems. Section 3 complements this nexus by providing both conceptual and real-world examples of potential application areas, as well as the ways in which GIScience could, methodologically and technically, inform a GeoAI-based approach to the planning, design and management of smart cities. Section 4 discusses the potential role of city planning in implementing smart-city agenda and defines a human-centered city planning framework leveraging GeoAI to fulfill four smart-city policy goals. This section also presents four research themes illustrating the potential application of GeoAI in elevating city planning activities. The concluding section strives to highlight the challenges in the application of GeoAI in city planning and identify potential avenues for future research.

2. Geospatial Artificial Intelligence (GeoAI): A potential technology solution for smart-city problems

Smart cities thrive on the integration of physical and digital layers of infrastructure. Different models have been proposed to illustrate the architecture of this integrated system, focusing on the societal issues (Batty et al., 2012; Degbelo et al., 2016), the network of embedded objects (Rathore et al., 2016; Silva et al., 2018), and the structure of information systems (Li et al., 2020; Yin et al., 2015). In all these models, the digital framework of the smart city, supported by Information and Communications Technologies (ICTs), relies on technological breakthroughs in three domains: big data, computational algorithms, and (super-)computational infrastructure. The rapid growth of big data in the past two decades is the outcome of advances in Earth Observation (EO), Wireless Sensor Networks (WSNs), Internet and Communications Technologies (ICTs), social media platforms, and wireless technologies which have generated massive volumes of unstructured data at different spatial, temporal, and social scales (Batty, 2013b; Goodchild, 2019; Li, 2020). Kitchin (2014a) suggests that big data consists of voluminous, dynamic, varied, all-encompassing, granular, low-cost, and inter-relatable datasets that are flexible in their "extensionality" and "scalability."

Depending on the source, big data could be directed, automated, or volunteered. Directed data are produced by means of "passive" technological devices generating, for instance, 2D or 3D scanning of the physical environment, objects and people— such as satellite imagery and LiDAR point clouds. Automated data, on the other hand, are generated by the automatic function of "active" devices or systems, such as the network of wireless sensors, also known as the Internet of Things (IoT) (Rathore et al., 2016), and wireless technologies— including Wi-Fi hot spots, mobile phones, and RFID (Radio Frequency Identification) (Li et al., 2020). Volunteered data, also known as crowdsourced data or Volunteered Geographic Information (VGI (Goodchild, 2007),), are generated by users on a public platform, such as social media. In general, Big data complements the traditional, authoritative types of information, such as remote sensing imagery and census data, which have historically been used to simulate, plan, design, and manage cities (Boeing, 2021; Crooks et al., 2015; Kitchin, 2014a).

Recent developments in computational algorithms, such as Artificial Intelligence (AI), and particularly Deep Learning (Razavi, 2021), not only have resulted in the resurgence of a scientific field, known as Data Science, but also have made possible the collection, processing, analysis, and visualization of big data. Moreover, the increased availability of computational infrastructure, such as Graphics Processing Units (GPU) and cloud computing platforms, have facilitated the rapid growth of big data applications (Li, 2020).

An interdisciplinary spatial analytical field, known as Geospatial Artificial Intelligence (GeoAI), has recently emerged at the convergence of GIScience/GIS and the three foregoing technological revolutions. GeoAI is a technology solution to data-and computing-intensive geospatial problems and heralds a new phase of data-intensive exploration, complementing the empirical, theoretical, and computational paradigms that hitherto, sequentially, characterized the evolution of scientific research (Gahegan, 2020; Li, 2020). From an epistemological standpoint, GeoAI relies on two methodological threads: the knowledge-driven, top-down approach, and the bottom-up, data-driven framework. The latter is an inductive process, which relies heavily on Machine Learning (ML) techniques and has become the conventional methodology in GeoAI due to its ability both to reveal hidden patterns within big data and to make predictions. As a frontier in the Machine Learning field, Deep Learning models, such as Convolutional Neural Networks (CNNs), have gained popularity due to their robust feature extraction and precise projection capabilities (Janowicz et al., 2020; Razavi, 2021). Contrary to the data-driven approach, the top-down methodology uses deductive reasoning and relies heavily on prior knowledge, also known as domain knowledge, as well as on pre-existing logical rules and constraints to simulate real-world entities and to draw inferences (Batty, 2013b; Hogan et al., 2020).

As such, GeoAI could serve as a potential solution framework to address the multifaceted geospatial problems facing smart cities. Indeed, the complexity of smart-city problems calls for a hybrid approach that not only integrates both inductive and deductive methodologies, but also informs and is informed by theory. The following section gives an overview of the application areas where GeoAI could draw from the broader scientific field of GIScience to tackle the major challenges that smart cities encounter.

3. GIScience tools for smart cities

In addition to big data, Artificial Intelligence, and advanced computational infrastructure and techniques, GeoAI could utilize a whole array of methodological and technical tools that Geographic Information Science and Systems have to offer. This section outlines the tools and analytical frameworks within GIScience that have potential to inform a GeoAI-based approach to the planning, design, management, analysis, and simulation of smart cities.

3.1. Critical GIS

The intellectual and societal critiques of Geographic Information Systems in the early 1990s—compiled in John Pickles' anthology *Ground Truth* (1994) — resulted in the emergence of a subfield called Critical GIS (Goodchild, 2019). As researchers in this field have shown, Critical GIS can enable progressive social transformation by revealing spatial configurations of power, by creating alternative geographies of possibility, and by generating new digital spatial knowledge. Examples include the mapping of community-based, not-for-profit “solidarity economy” and the geography of “worker cooperatives” across the United States (Pavlovskaya, 2006, 2018). On the intellectual front, Critical GIS has potential to tap into the emerging internet-based geospatial tools and computational techniques to model a non-Cartesian space in GIS in order to visualize processes, experiences, relations, and phenomena that cannot be represented by the absolute, cartesian space of the conventional GIS. Graph layout heuristic and blockmodeling techniques, for instance, utilize interaction matrices and network representations, respectively, to reformulate the cartesian space of mainstream GIS and the associated geographical concepts— such as polygon, region, proximity and distance— to a non-Euclidean, relational space. Thanks to these stochastic methods, researchers are now able to visualize complex relations, including flights network based on the OpenFlights dataset, and daily mobility of people, such as origin-destination commuter flows for the California Bay area (Bergmann & O'Sullivan, 2018).

3.2. From Public Participation GIS to NeoGeography

Since the 1990s, GIS has extensively been used to engage stakeholders, interest groups, and members of the public in land-use and environmental planning and decision-making processes. The concepts of Participatory GIS (PGIS) and Public Participation GIS (PPGIS)—representing bottom-up and centralized approaches, respectively— have been frequently employed to describe varying levels and mechanisms of public engagement efforts in the planning and decision-making structures (Brown et al., 2014; Brown & Kyttä, 2014). In the wake of big data, the concepts of Volunteered Geographic Information (VGI) (Goodchild, 2007) and Ambient Geographic Information (AGI) (Stefanidis et al., 2013) have appeared in the literature to refer to the geospatial data generated by users on social media platforms and web-based applications.

VGI is spatially explicit crowdsourced data which are directly available through Web 2.0 applications and GPS-enabled sources, such as maps created by users on social media, as well as tracking and location-based services. AGI, on the other hand, is spatially implicit crowdsourced data embedded in various sources and as such should be derived from content through intelligent geo-computational techniques. VGI and AGI have been used to derive implicit urban forms and functions and to reveal micro-geographies, such as colloquial footprints, which cannot be visualized from authoritative data sources (Crooks et al., 2015). VGI and AGI, which will constitute the cornerstone of the smart city, have given rise to a new practice of geographic knowledge production, or what Michael Goodchild terms NeoGeography (Goodchild, 2019).

3.3. Real-time GIS and digital twin

There is a general consensus in the literature around the central role that GIS-enabled data analytics, operating in or near real time, could play in the monitoring and operation of the smart city (Batty, 2013; Kitchin, 2014a, 2014b; Li et al., 2020), in disaster risk management (Zerger & Ingle Smith, 2003), and in public engagement efforts (Sun & Li, 2016). Li et al. (2020) suggest that the main architecture of the real-time GIS network comprises ICTs, big data, and real-time geoprocessing, real-time simulation and analytics, and real-time data visualization. ICTs constitute the foundational infrastructure of the smart city, facilitating transfer of data from various devices to the main data center and allowing data to move effectively and efficiently across the IoTs (Li et al., 2020). The continuous stream of directed, automated, and volunteered big data harvested from a wide range of mobile and fixed data sources, physical and social sensing, about buildings, assets, urban infrastructure, citizens, and the environment enables a real-time simulation of urban systems at various spatial, temporal and social scales, constituting what Michael Batty once called the "digital twin" of the smart city (Batty, 2018). The simulation techniques deployed in real-time GIS should have the capacity to capture various interconnections and linkages across different strata of big data. As such, advanced simulation methods, such as Agent Based Models (ABM), Cellular Automata (CA), microsimulation, and network models— which are popular modeling frameworks in the complex systems science— can be tapped into to better inform the modeling and simulation of the smart city (Li et al., 2020; Van Schrojenstein Lantman et al., 2011).

Big Data compiled from different sources in real time need to be effectively visualized and communicated to public officials, stakeholders, city planners, and the public. Depending on the nature of the geo-spatial data, visualization products can take different forms including spatial, space-time (Berthe et al., 2020), multi-variate, temporal, and dashboard (Kitchin, 2014b; Kitchin et al., 2014c; Rivard & Cogswell, 2004). In order to handle the voluminous deluge of urban big data in real time, a web of computers connected through a high-speed communication network, known as cloud computing, should be devised. Therefore, computationally intensive tasks are distributed among smaller high-performance computers. The real-time geoprocessing component of the smart city consists of NoSQL database, distributed and parallel computing, streaming architecture, and real-time prediction (Kitchin et al., 2017; Li et al., 2020).

Employing this framework, Dembski et al. (2020) developed a prototype digital twin for the small town of Herrenburg, Germany. The prototypical platform combined a 3D model of the urban fabric and simulations of the street network, urban mobility, and wind flow with VGI data. This digital model was implemented in a Virtual Reality (VR) environment and used in various public participation processes to address urban challenges, such as traffic and air pollution. The results of a public survey indicate that the urban digital twin could better enhance decision-making and consensus-building processes relative to conventional public participation efforts (Dembski et al., 2020).

3.4. Spatial Decision Support Systems

One of the major applications of GIScience in the planning, design and management of smart cities has been manifested through the integration of GIS with modeling techniques to support the design and evaluation of decision alternatives, giving rise to a whole array of tools called Spatial Decision Support Systems (SDSS) or Planning Support Systems (PSS) (Keenan & Jankowski, 2019). The former concept refers to the tools that are employed to address short-term spatial problems, while the latter represents the platforms employed to tackle long-term, strategic planning tasks (Geertman et al., 2015). The concept of SDSS has evolved since its inception in the mid-1980s from a closed, stationary joint product of GIS and Decision Support Systems (DSS) into the concept of dynamic decision support systems, relying on authoritative and crowdsourced data, open knowledge networks, and inferencing mechanisms enabled by Artificial Intelligence methods (Gordon et al., 2021; Keenan & Jankowski, 2019).

Many applications of SDSS entail the design and evaluation of spatial decision variants (alternatives), as well as some form of resource allocation. Two specialized methodologies of SDSS include: 1) Spatial optimization and 2) Multicriteria Spatial Decision Support Systems (MC-SDSS), also known as GIS-based Spatial Multicriteria Decision Analysis (GIS-MCDA) methods (Malczewski & Rinner, 2015). Spatial optimization employs the optimization techniques of mathematical programming to structure and find solutions to problems in which spatial arrangement (pattern) is crucial (Tong & Murray, 2012). MC-SDSS, on the other hand, combines spatial and non-spatial data, subjective and objective elements of problem evaluation, modeling techniques of the decision science and location science, as well as the analytical and visualization functions of GIS into an interactive system to assist decision-makers in effectively and efficiently evaluating spatial alternatives. These two methods have been extensively used in various urban planning tasks, ranging from land-use planning to transportation planning and routing, to location-allocation planning and facility siting, to school districting (Cao et al., 2020; Malczewski & Rinner, 2015).

The efficacy of SDSS in addressing planning-related challenges has been documented in the literature. For instance, in a recent study, Torabi Moghadam and Lombardi (2019) utilized a MC-SDSS tool derived from a GIS-based scenario planning and visualization tool, known as CommunityViz— an ArcGIS extension—to help stakeholders develop an urban energy planning strategy to enhance the energy performance of residential building stocks, reduce carbon emissions, and meet long-term sustainability goals. In a different context, Dionisio et al. (2020) found that implementing SDSS tools through the collaborative partnership model of engagement and communication between the research team, the planning stakeholders, and the public enables planning authorities to promote cross-sectorial, multi-scalar and inclusive approaches to urban regeneration. Researchers have also outlined the potential barriers to the implementation of SDSS tools. For instance, Uran and Janssen (2003) found that in addition to the complexity of some SDSSs, scant support for the evaluation of the output, such as the lack of sensitivity analysis and a clear ranking mechanism for alternatives, could impede the successful implementation of SDSS tools. Pearman and Cravens (2022) also suggest that institutional and organizational hurdles, to a large degree, account for the limited usability of such tools.

The rise of big data and GeoAI has presented opportunities and challenges to the SDSS methods. It has encouraged researchers in the field to gradually transition from using small datasets to utilizing big data sources, such as smart phones, smart card transactions, and the IoTs. This shift poses a methodological challenge, since it raises the complexity level of decision space in optimization models, calling for remaking the formulation structure, as well as the traditional solution techniques used for various planning tasks. Moreover, GeoAI enables a shift from static to dynamic, or real-time, optimization models which are applicable to the optimization problems in the context of smart cities. The potential research areas under the new paradigm could include combining machine learning techniques, big data, and spatial optimization models to generate time-sensitive routes to avoid poor air quality while traveling in urban areas (Zou et al., 2020); planning an evacuation route in the midst of a natural disaster event based on smart mobile phone location data leveraging both knowledge-based and data-driven approaches (Yin et al., 2020); and, devising a computational technique to efficiently solve a large "p-median" problem using parallel high-performance computers (Mu & Tong, 2020).

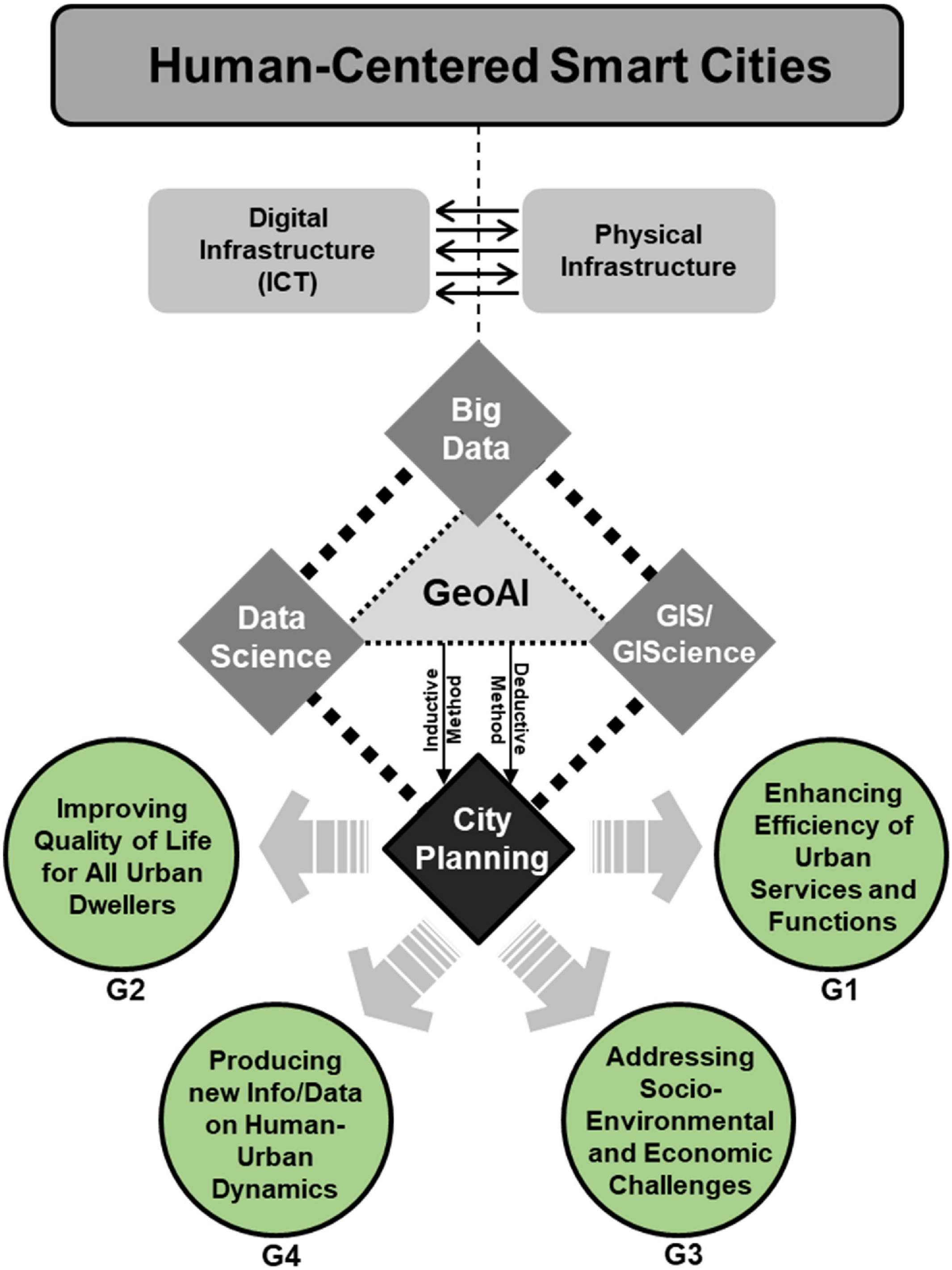

Fig. 1. Schematic diagram portraying how City Planning could leverage the synergies between GIScience/GIS, Data Science, and Big Data to meet four overarching smart-city goals. This framework, organized around human-centered city planning principles, addresses the present and future challenges facing cities and represents a more holistic alternative to the technocratic view of the smart city. (Source: Authors).

3.5. GeoDesign

Over the past decade, a spatial decision support methodology, known as GeoDesign, has drawn attention in city planning circles. GeoDesign integrates design and science, and uses GIS-based analytic, data exploration and visualization capabilities to help create and explore alternative future design scenarios in a collaborative environment (Foster, 2016; International GeoDesign Collaboration, 2020; Steinitz, 2012). For instance, in a recent study, Davis et al. (2020) illustrate how GeoDesign could be used as a planning tool to integrate the needs, values, and traditions of indigenous communities with the contemporary methods of city planning. Taking a land-use plan for the Navajo Nation's Dilkon community in Northeastern Arizona as a case study, the findings suggest that the GeoDesign framework not only allowed indigenous community members to voice their concerns in the land-use planning process, but also empowered them to use the indigenous traditions, customs, and cosmologies in the decision-making and consensus-building processes while meeting critical community needs, such as affordable housing, job creation, etc. The GeoDesign planning framework also fostered a sense of transparency and trust in the planning process that was hitherto absent in land-use planning efforts in American-Indian communities (Davis et al., 2020).

4. Towards a GeoAI-enabled, human-centered city planning framework for the smart city

Thus far, we have discussed the ways in which GIScience could offer methodological and technical contributions to a GeoAI-based approach to smart-city problems. However, the outstanding question is, how could smart cities activate and operationalize the potentiality of Geospatial Artificial Intelligence to create sustainable, resilient, equitable, healthy, and connected places and communities? This section aims to address this question through the prism of city planning and to bring the planning discipline back into the smart-city discourse. As mentioned earlier, planning concepts (e.g., smart growth) used to occupy a central position in the initial conception of the smart city. However, the rise of smart technologies and their associated by-products, such as automation, efficiency, and standardization—among others, gradually relegated planning to the backdrop and overshadowed the traditional role of urban planners that used to act as intermediaries between technological innovations and urban processes (Cowley & Caprotti, 2019; Karvonen et al., 2020; Morgan & Webb, 2020). We contend that GeoAI could enable city planning to utilize the synergies between Big Data, Data Science, and GIScience to play a key role in the planning, design, management, and monitoring of the smart city. Acknowledging the major critiques, challenges, and risks associated with the smart city concept—i.e., the technocratic mode of governance and the neoliberal economic ideals (Lee et al., 2020); marketization and corporatization of city planning, urban management and public services (Carr & Hesse, 2020); ethical and social issues with respect to surveillance, equity, and individual privacy (Kitchin, 2021), we are aiming to formulate a human-centered approach as an alternative vision to the techno-centric concept of smart cities.

Drawing on previous research and initiatives, such as the Programable City Project ((https://progcity.maynoothuniversity.ie/), Kitchin, 2014a) and the FuturICT Initiatives ((https://futurict2.eu/); Batty et al., 2012) that put fundamental human values— such as privacy, fairness, democracy, and citizenship— at the core of their framings, and considering the desired outcomes envisioned for smart cities— including productivity, livability, governance, and sustainability (Kim et al., 2021; Yigitcanlar et al., 2018), we propose an integrated conceptual framework that illustrates how the symbiosis between city planning (encompassing urban design, urban planning, and urban management) and the three techno-scientific constituents of GeoAI could help achieve four major smart-city policy goals. These goals include: 1) enhancing the efficiency of urban services and functions; 2) improving quality of life for all urban citizens; 3) addressing the pressing socio-environmental and economic challenges that could plague urban systems on different levels; and, 4) contributing to the production of spatial data, information and knowledge on human-environment dynamics (See Fig. 1).

Improving the efficiency of urban functions and services is a technical problem which has traditionally been one of the main objectives of urban planning and management. Urban services and functions include all the amenities, facilities, and infrastructures that governmental bodies, independently or in collaboration with private entities, deliver to urban dwellers, such as water, sewer and stormwater systems, public transit, green space systems, and affordable housing—among others. As Zhang et al. (2017) and Kuller et al. (2021) in the latter part of this section (Green Infrastructure Research) demonstrate, GeoAI could be utilized for the betterment of the delivery of such urban infrastructures on different scales in the context of future smart cities. The second policy goal is a normative and ethical problem; it concerns the variegated aspects of urban design and placemaking practices affecting the spatial configuration of cities and urban form vis-à-vis social equity and well-beings of people, as well as the ways in which people perceive, live and experience the built environment. Examples presented in this section (Urban Vibrancy Research) by Botta and Gutiérrez-Roig (2021) and Zhou et al. (2019) exhibit how GeoAI could be utilized to enhance livability and equity in smart cities by revealing the association between subjective parameters and the socio-spatial structure of the urban environment.

Recent research reports on the widening gaps between smart-city initiatives and sustainability goals (Evans et al., 2019). Thus, the third goal in our proposed GeoAI-enabled city planning framework is focused on the role of urban planning in addressing the critical urban challenges that future smart cities will encounter, as well as the societal, ecological, economic, and spatial implications of such problems in reference to sustainability principles. Research projects presented in the second half of this section (Modeling Sustainable Urbanism) by Mirzabeigi and Razkenari (2022) and Yao et al. (2018), for instance, demonstrate how GeoAI combined with sustainability frameworks could help tackle pressing urban challenges and enhance the planning practice. Last but not least, as the recent studies suggest (Boeing, 2021; Crooks et al., 2015), in the wake of GeoAI, generating insights into the human-environment nexus is no longer the exclusive purview of such fields as urban geography or environmental psychology. In fact, as illustrated in the last part of this section (Urban Morphology Studies), city planning and its subfields could take a leading role in producing spatial data, information and —ultimately— new knowledge on human-urban systems which could inform the planning practice, as well as the other three smart-city policy goals.

What follows exemplifies the research efforts that elucidate how a GeoAI-enabled city planning approach could help accomplish the four policy goals presented earlier.

4.1. Bettering urban services and functions: Green Infrastructure Research

The rapid pace of auto-oriented urban development in the United States in the second half of the twentieth century, particularly in the form of urban sprawl, is regarded as the main cause of a wide range of adverse social, economic, ecological, and public health outcomes. One of the most significant aspects of this process is the conversion of green fields into intense built-up areas with high percentage of impervious surface, e.g., roads, parking lots, and buildings. This has led to a modified thermal climate in highly urbanized areas, particularly at night, forming what is termed Urban Heat Island (UHI) (Santamouris, 2013). Daytime and nighttime UHI effects, which have significant implications for urban sustainability— in terms of energy and water consumption, greenhouse gas emissions, health outcomes, and environmental impacts— are more pronounced in semi-arid regions. Provision of green infrastructure— a web of open space fully or partially covered by grass, shrubs, trees, and other vegetation— is regarded as one of the strategies to mitigate the UHI effect. A large body of research utilizing different elements of GeoAI demonstrates that the direct and indirect cooling benefits of green space are highly effective in reducing diurnal air temperatures in urban areas.

Zhang et al. (2017) aim to contribute to this corpus of knowledge by exploring the linkages between the spatial arrangement of green infrastructure and its cooling effects at the local and regional scales. To this end, Zhang and colleagues measure the agglomeration of cooling benefits, i.e., neighborhood cooling resulting from adjacent green spaces, and offer an optimal spatial arrangement of green infrastructure to maximize its mitigation impacts on diurnal UHI variations in the context of the City of Phoenix, Arizona. In doing so, Zhang and colleagues introduce an analytic framework combining remote sensing, GIS, spatial statistics, and multi-objective spatial optimization modeling. The study area selected for this research is an urban district, 8800 ha in size, with a high percentage of low-income households. The results suggest that optimal green space siting in the study area may result in 1–2° and 0.5 °C reduction in average local and regional air temperatures, respectively. This is a significant cooling effect considering the miniscule portion of the total new green spaces relative to the size of the study area (total green space accounts for 1.3% of the study area) (Zhang et al., 2017).

Besides the Urban Heat Island effect, high levels of impervious surfaces in urbanized areas have disrupted the natural water cycle in local and regional hydrologic systems. The efficient management of the storm water runoff in urban areas is one of the challenges facing local governments. Historically, surface or underground drainage systems, known as grey infrastructure, were laid to transport the storm water runoff either to treatment plants or to natural water basins. However, with the increased infiltration of pollutants into water resources such stormwater management concepts as Low Impact Development (LID) and Green Storm Water Infrastructure (GSI) have emerged in city planning circles (Eckart et al., 2017). GSI, representing a sustainable approach to the question of stormwater management, is an interconnected system of green space that utilizes natural features and permeable landscaping to filter and use stormwater in situ. With the increased intensity and frequency of natural hazards in recent years, GSI is considered a critical component of the urban infrastructure that makes cities more resilient to the impacts of climate change (The U.S. Environmental Protection Agency, 2021).

The ideal planning process for GSI should take account of a broad range of hydrological, socioeconomic, urban fabric, and ecological variables to identify suitable locations while maximizing the system's overall impacts. Different studies have utilized Geospatial technologies and spatial analytical techniques to study the spatial configuration and siting of GSI at various scales. For instance, Kuller et al. (2021) analyzed the spatial structure, as well as the level of service of a Water-Sensitive Urban Design (WSUD) infrastructure, which is the Australian version of GSI, across a river catchment in Sydney, Australia at two spatial scales. On the micro level, Kuller and colleagues employed univariate statistical analysis techniques to scrutinize the extent to which each suitability variable, i.e., socioeconomic, biophysical, and urban fabric metrics, affects the location of each type of WSUD assets. The researchers also utilized a spatial suitability analysis tool, known as SSANTO, to assess the degree of strategic placement of WSUD assets on the catchment level, that is, the difference between the optimal suitability configuration for the WSUD assets, based on the SSANTO suitability maps, and the current spatial layout of the WSUD infrastructure. The findings suggest that most suburbs in the region have low WSUD coverage. Moreover, socioeconomic variables were not taken into account in the planning and placement of existing WSUD assets as there was a disproportionately low presence of WSUD assets in residential areas. The results of the suitability analysis also indicate that the spatial implementation of the WSUD infrastructure was the product of ad-hoc planning and opportunistic measures rather than of strategic planning and visioning (Kuller et al., 2021).

4.2. Advancing livable and equitable places: Urban Vibrancy Research

A large body of scholarship has also utilized different elements of GeoAI to improve the livability of the urban environment for all segments of the urban population. Various metrics are employed to create livable and equitable places and communities. Thanks to Jane Jacobs' *The Death and Life of Great American Cities* (1961), the notion of urban vibrancy entered the vocabulary of New Urbanism and has become one of the main metrics of human-centered urban design and placemaking practices. A vibrant urban environment refers to an urban space that fosters high levels of urban activity and human interactions. Relying on authoritative and crowdsourced data, as well as advanced spatial modeling, Botta and Gutiérrez-Roig (2021) aimed to identify the components of the built environment that contribute to urban vibrancy. In doing so, the researchers combined a large dataset on the presence of mobile phone users from different age groups in seven Italian metropolises with the data derived from the Italian census agency as well as OpenStreetMap to reconstruct urban vibrancy and its constituting urban planning features. Such features include diversity index, Points of Interest (POIs), road intersections, age and height of buildings, and the density and intensity of buildings and population. The findings at the aggregate and city levels suggest that all the urban features, with the exception of the diversity of building ages, have a strong relationship with the density and presence of people—used as proxies for urban vibrancy. Also, the association between urban features and urban vibrancy remains consistent across spatial scales and population age groups, implying that urban elements that foster vibrancy could have a universal effect (Botta & Gutiérrez-Roig, 2021).

Similar to urban vibrancy, walkability is another metric used by city planners and urban designers to measure the livability of the urban environment. Walkability is also an indicator of the potential for nonmotorized mobility and a car-free lifestyle in a given neighborhood, with implications for public health, fossil fuel consumption and the environment. While most walkability studies focus on the objective attributes of the built environment that purportedly facilitate walking to destinations— such as the characteristics of the street network, the spatial distributions of PoIs, a mix of land uses, among others— the "friendliness" of the built environment and subjective norms have not received enough attention. Zhou et al. (2019) utilized street view imagery along with the recent developments in sensing and computing technologies to understand the visual characteristics of streetscapes, or what they term "street visual walkability." Proposing a four-dimensional conceptual framework to approximate visual walkability, including psychological greenery, visual crowdedness, outdoor enclosure and visual pavement, Zhou and colleagues derive street view imagery from Baidu Map Street View (BMSV), a repository of street view imagery for Chinese cities, and utilize a convolutional neural network (CNN) technique— a deep learning algorithm known as Seg-Net— to detect, extract and classify different physical features in each image. The findings suggest that the Integrated Visual Walkability Index— that is, a composite metric developed in this study as a proxy for the human perception of the quality of the built environment for pedestrian activity— proves to be an effective indicator of street visual walkability. Moreover, spatial regression shows a strong correlation between socioeconomic characteristics of neighborhoods and the mean value of the Integrated Visual Walkability Index. This implies that in the context of this study (City of Shenzhen, China), there is a great disparity in the quality of streetscapes between rich and poor neighborhoods (Zhou et al., 2019).

4.3. Addressing critical urban challenges: Modeling Sustainable Urbanism

Several studies have integrated sustainability frameworks with GeoAI to tackle pressing urban challenges and enhance the planning practice. Land-use planning, for instance, is one of the major efforts in city planning, having significant implications for economy (e.g., energy consumption and infrastructure costs), society (public health, urban microclimate, and segregation) and the environment (e.g., depletion of natural resources, conversion of agricultural land, and pollution) (Lord et al., 2015). The notion of sustainable land-use planning, which has gained traction since the 1990s both in academia and in practical applications, not only seeks to strike a balance between economic growth, ecological impacts, efficient land resource allocation, and societal benefits, but also concerns with the strategic alignment of land-use categories, transportation networks, employment opportunities and housing plans. Several studies propose novel spatial optimization approaches to support sustainable land-use allocation activities. For instance, Yao et al. (2018) formulate an optimization model that incorporates the main spatial features of the sustainable land-use planning, i.e., contiguity, compactness, and compatibility, into an individual or hybrid optimization model, namely, knapsack or threshold model, or a combination of the two. Stressing the challenges associated with modeling such spatial characteristics, Yao and colleagues maintain that the complexity of sustainable land-use planning problems calls for employing multi-objective optimization modeling. Strategies in this field include finding non-inferior solutions and consolidating multiple objectives into composite objectives, as well as using exact algorithms versus heuristics (Yao et al., 2018).

Generating multiple optimal land-use plans is important in the city planning practice, especially when the implementation of certain optimal solutions is not feasible due to real-world constraints. The rise of GeoAI has also made possible the formulation of spatio-temporal optimization models. In the context of land-use planning problems, this means optimizing not only the location and the amount of a land-use category to be assigned to that location, but also "when" and "how" the transition to the specified land use targets should happen over time (Cao et al., 2020).

Modeling and enhancing energy performance of building stocks is one of the sustainability goals outlined in all smart-city programs. In a recent study, Mirzabeigi and Razkenari (2022) utilized Grasshopper, Ladybug, and Eddy3D— a set of simulation tools used for the modeling and analysis of solar radiation and microclimate— to develop a multi-stage optimization framework for evaluating building energy performance and outdoor thermal comfort for urban typologies in Syracuse, NY. This approach, which helps identify optimal urban design solutions, has also great implications for the wellbeing of urban populations. The findings indicate that mid-rise multi-family buildings demonstrate the best performance on both criteria compared to other typologies. In another study, Torabi Moghadam et al. (2018) proposed a novel modeling methodology, known as city architype, that integrates GIS with a deterministic method to simulate and predict energy consumption patterns and evaluate energy planning scenarios at an urban scale. The proposed model incorporates an engineering-based method to assess future urban refurbishment scenarios and calculate energy demand, as well as microclimatic conditions of the city based on a 3D simulation of the urban environment. The model was used to evaluate two refurbishment scenarios for a middle-sized Italian city in the Turin Metropolitan Region. The ideal scenario that maximizes energy savings is then visualized in a GIS environment to help planning authorities identify the building stock that is in urgent need of renovation (Torabi Moghadam et al., 2018).

4.4. Generating new knowledge on urban dynamics: Urban Morphology Studies

A growing body of scholarship leverages GoeAI to generate new insights into human-urban dynamics through monitoring, analyzing, and modeling urban morphology. Urban morphology is conceived of as the interplay of urban form and function. It represents the texture, grain, and spatial order of the city, as well as the ways in which people use and navigate urban space as part of their daily activities (Boeing, 2021; Crooks et al., 2015). Not only does the study of urban morphology help to understand urban dynamics, it has implications for urban design, resource allocation, and transportation planning. Utilizing crowdsourced data, these studies take a bottom-up approach to reconstruct spaces of everyday life, in particular the representational space—to borrow an element from Henri Lefebvre's spatial triad (Lefebvre, 1991). For instance, Crooks et al. (2015) use crowd-harvested data in the form of VGI and AGI to study traffic patterns, as well as public sentiments and perception of neighborhoods. The findings suggest that crowdsourcing makes possible the study and modeling of urban morphology at much finer spatial, temporal and social scales, and enables the smart city to monitor the dynamic changes as they occur within the city and to model urban systems in a more realistic manner (Crooks et al., 2015).

On the urban function front, Diao et al. (2016) propose a hybrid method to visualize and analyze the landscape of urban daily activities through the traces of cell phones. By combining an activity detection model, known as multinomial logistic regression model, with travel diary surveys in the Boston metro area, Diao and colleagues reveal the hidden activity information on individual behaviors and formulate generalizable rules about mobility and "urban activity landscape." Analyzing the activities of more than 20,000 frequent mobile phone users in the Boston Metro Area during four consecutive months, the resultant model provides a vivid illustration of the spatio-temporal human dynamics in the region. For instance, the activity profile generated for individual locations offers a more granular characterization of urban space and its relation to human activities across various time frames compared to conventional land use-based approaches (Diao et al., 2016).

In a recent study, Boeing (2021) uses OSMnx, that is, an open-source Python toolkit which he has developed to analyze street networks, along with geographical data obtained from OpenStreetMap (OSM) to analyze various characteristics of the urban fabric, such as street network patterns, orientations, and spatial configurations. Contextualizing his work in the analytical cartography and the visual culture of city planning, Boeing combines quantitative (urban data analytics) and qualitative (interpretive and narrative) methods of urban morphology with urban big data. He employs two cartographic methods to visualize the urban morphology through street networks. The first method uses the OSMnx toolkit to generate one-square-mile figure-ground diagrams of street networks and building footprints for 12 global cities. The second technique uses polar street orientation (compass bearing) histograms, known as rose diagrams, for 25 cities around the world. This method illustrates the spatial structure of "urban circulation infrastructure" and the degree of entropy— that is, the amount of deviation from the "spatial-ordering logic" of the city's major grids— representing city planning and design histories. Such cartographic techniques enable city planners to showcase comparative urban forms and patterns and to simplify complex city planning and urban design concepts by making them visually comprehensible to the public. The visualization of spatial information in this manner, which makes hidden urban patterns legible, could play a vital role in better engaging and empowering citizens, advocacy groups and community-based organizations in collaborative and participatory planning and decision-making processes (Boeing, 2021).

5. Conclusion

This paper intends to engage with the ongoing debates on the role of planning in twenty-first century smart cities (Karvonen et al., 2020) and to make a case for a reconceptualization of the techno-centric notion of the smart city. In doing so, the paper proposes a human-centered framework for the smart city that leverages the synergies between City Planning and the scientific domains of Big Data, Geographic Information Science and Systems, and Data Science—which collectively constitute an emerging field known as Geospatial Artificial Intelligence (GeoAI)— to accomplish four broad policy goals: 1) to enhance the efficiency of urban services and urban functions; 2) to improve the quality of life for all urban citizens; 3) to address the pressing societal, ecological and economic challenges that could plague urban systems on different levels; and, 4) to contribute to the production of spatial data, information and knowledge on human-environment dynamics. Through various empirical examples and research efforts, the paper demonstrates that our proposed human-centered, GeoAI-enabled city planning framework is capable of addressing both technical-instrumental problems, as well as socio-political, normative, and ethical issues facing present and future cities, thus laying the groundwork for an alternative vision of smart urbanism.

Two points are worth noting here. Firstly, our proposed framework is grounded in the notion that the planning discipline should play a more prominent role in the planning, design and management of future smart cities run partially or entirely by the networked computing and digitally embedded instruments and technologies. Planning is arguably well-positioned to look at the 'big picture' when evaluating the immediate and long-term economic, ecological, societal, and spatial impacts of smart-city agenda and is capable of integrating human factors, collaborative governance, and context-sensitive parameters into the processes of planning, design and management of smart cities. As such, we argue that planning should play a major role in the implementation of smart-city technologies, including GeoAI, to safeguard the broader public interest, as well as the needs of vulnerable populations. However, we acknowledge that these views might not be universally shared among academics and that the role of planners in future smart cities is still open to debate. Moreover, other disciplines might reign supreme in varying aspects of private/public life in which planners traditionally have been heavily involved.

Secondly, over the past decade, many academics have made tremendous efforts to bridge the historical chasm within the planning discipline between design-based, physical planning— or what is known as city planning or urban design, and the policy-based, socioeconomic planning, which is conventionally termed urban planning (Banerjee, 2014; Gleye, 2015). Moreover, the increased public interest in livability and quality of life in urban areas, coupled with the rise of zoning reforms, in particular the growing adoption of form-based code, has created new conditions to reconcile the design-oriented and policy-based realms of planning. Inspired by these developments, this paper is also advocating for a holistic approach to urban issues and conceptualizes planning as a discipline that integrates urban design with urban planning. Nonetheless, we acknowledge that achieving the desired unity within the field is an elusive goal. Undoubtedly, planning professionals come from different backgrounds and might pursue diverse research interests and specialties within the field and even view the built environment through different lenses (Wyatt, 2004). It is also our conviction that defining a clear vision and well-delineated policy goals for planning will help converge different practices and research efforts within the field. In fact, the four policy goals outlined in the paper correspond to different branches of planning and encourage collaboration across the field. Moreover, the research projects cited in the paper demonstrate that GeoAI has generated huge opportunities for partnership not only among practitioners and academics within the field, but also between planners and scholars from other disciplines. The potential impact of GeoAI on the integrity of the planning discipline could be the subject of future research.

Through multiple analytical and empirical examples, the paper also illustrates the ways in which GIScience could, methodologically and technically, inform a GeoAI-based approach to the planning, design and management of smart cities. For instance, our analysis indicates that Critical GIS could enhance any GeoAI-based analytical framework that deals with smart cities because Critical GIS offers novel socio-spatial and technical tools not only to better visualize spaces of flows, relations, and networks—which are the governing principles of the digital city (Batty, 2013a)— but also to promote equity and social justice as the core values of future smart cities. The paper also sheds light on the challenges facing smart cities in the implementation of GIScience tools. For instance, as we showed in Section 3, GeoDesign could serve as an instrumental planning support tool in the context of smart cities, since it not only facilities a horizontal, collaborative city planning framework to tackle multifaceted planning tasks in partnership with communities (i.e., co-design), but also creates a platform for meaningful civic engagement and deep public participation, and helps address acute challenges facing present and future cities, such as injustice, marginalization, and social exclusion. Nonetheless, we acknowledge that the success of GeoDesign, like any other SDSS tool, depends on a wide range of parameters, such as the degree of trust between community members and planning officials, the level of technical literacy and capacity within the community, and institutional and organizational barriers—among others, all of which could overshadow the application of planning support tools in real-world scenarios.

This paper also raises several potential lines of inquiry at the intersection of City Planning, GeoAI and Big Data: How can public officials utilize GeoAI to identify health disparities, to carry out community needs assessment and effectively allocate resources, or to predict socioeconomic changes in a neighborhood, such as gentrification, and safeguard the interests of vulnerable populations? How could SDSS tools be deployed to optimize development incentives and public financing mechanism and identify suitable properties to help minimize the total development costs associated with affordable housing, while maximizing social and economic impacts? How could regional transportation agencies use GeoAI capabilities to plan a multi-modal transportation network with a view to enhancing connectivity and accessibility to housing, public services and job opportunities and cutting GHG emissions, as well as optimizing both regional growth impacts and return on investment? How can SDSS be utilized to identify ecologically sensitive areas and human settlements that might adversely be impacted by climate change, and how can city planners develop scenarios to mitigate adverse effects, plan for post-disaster recovery, and accommodate the potential displacement of vulnerable communities?

Conflicts of interest

The authors declare no conflict of interest.

References

Banerjee, T. (2014). General introduction. In T. Banerjee (Ed.)*, Vol. 1. Urban design: Critical concepts in urban studies* (pp. 1–24). London, UK: Routledge. The Idea of Urban Design.

Batty, M. (2013a). *The new science of cities*. MIT Press.

Batty, M. (2013b). Big data, smart cities and city planning. *Dialogues in Human Geography, 3*(3), 274–279. https://doi.org/10.1177/2043820613513390

Batty, M. (2018). Digital twins. *Environment and planning. B, Urban analytics and city science, 45*(5), 817–820 (Web).

Batty, M., Axhausen, K. W., Giannotti, F., et al. (2012). Smart cities of the future. *The European Physical Journal - Special Topics, 214*, 481–518.

Bayat, A., & Kawalek, P. (2021). Digitization and urban governance: The city as a reflection of its data infrastructure. *International Review of Administrative Sciences*. https://doi.org/10.1177/00208523211033205

Bergmann, L., & O'Sullivan, D. (2018). Reimagining GIScience for relational spaces. *Canadian Geographer/Le Géographe Canadien, 62*, 7–14. https://doi.org/10.1111/cag.12405

Berthe, G., et al. (2020). Analysis and real-time visualization of geo-spatial data using Xdash: Application to flair project. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 43*(4), 775–779 (Web).

Boeing, G. (2021). Spatial information and the legibility of urban form: Big data in urban morphology. *International Journal of Information Management, 56*, Article 102013. https://doi.org/10.1016/j.ijinfomgt.2019.09.009

Botta, F., & Gutiérrez-Roig, M. (2021). Modelling urban vibrancy with mobile phone and OpenStreetMap data. *PLoS One, 16*(6), Article e0252015. https://doi.org/10.1371/journal.pone.0252015

Brown, G., Kelly, M., & Whitall, D. (2014). Which 'public'? Sampling effects in public participation GIS (PPGIS) and volunteered geographic information (VGI) systems for public lands management. *Journal of Environmental Planning and Management, 57*(2), 190–214. https://doi.org/10.1080/09640568.2012.741045

Brown, G., & Kyttä, M. (2014). Key issues and research priorities for public participation GIS (PPGIS): A synthesis based on empirical research. *Applied Geography, 46*, 126–136. https://doi.org/10.1016/j.apgeog.2013.11.004

Cao, K., Li, W., & Church, R. (2020). Big data, spatial optimization, and planning. *Environment and Planning B: Urban Analytics and City Science, 47*(6), 941–947. https://doi.org/10.1177/2399808320935269

Carr, C., & Hesse, M. (2020). When Alphabet Inc. plans Toronto's Waterfront: New post-political modes of urban governance. *Urban Planning, 8*(1), 69–83.

Cowley, R., & Caprotti, F. (2019). Smart city as anti-planning in the UK. *Environment and Planning D: Society and Space, 37*(3), 428–448.

Crooks, A., et al. (2015). Crowdsourcing urban form and function. *International Journal of Geographical Information Science, 29*(5), 720–741.

Davis, J., Pijawka, D., Wentz, E., & Hale, M. (2020). Evaluation of community-based land use planning through Geodesign: Application to American Indian communities. *Landscape and Urban Planning, 203,* Article 103880. https://doi.org/10.1016/j.landurbplan.2020.103880

Degbelo, A., Granell, C., Trilles, S., Bhattacharya, D., Casteleyn, S., & Kray, C. (2016). Opening up smart cities: Citizen-centric challenges and opportunities from GIScience. *ISPRS International Journal of Geo-Information, 5*(2), 16. https://doi.org/10.3390/ijgi5020016

Dembski, F., Woessner, U., Letzgus, M., Ruddat, M., & Yamu, C. (2020). Urban digital twins for smart cities and citizens: The case study of herrenberg, Germany. *Sustainability, 12*(6), 2307. https://doi.org/10.3390/su12062307

Diao, M., Zhu, Y., Ferreira, J., & Ratti, C. (2016). Inferring individual daily activities from mobile phone traces: A Boston example. *Environment and Planning B: Planning and Design, 43*(5), 920–940. https://doi.org/10.1177/0265813515600896

Dionisio, R. D., Schindler, M., & Kingham, S. (2020). Tools for sustainable change: How spatial decision-support tools support transformative urban regeneration. *International Journal of E-Planning Research, 9*(2), 21–42. https://doi.org/10.4018/IJEPR.2020040102

Eckart, K., McPhee, Z., & Bolisetti, T. (2017). *Performance and implementation of low impact development – a review* (Vols. 607–608) pp. 413–432). The Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2017.06.254

Evans, J., Karvonen, A., Luque-Ayala, A., Martin, C., McCormick, K., Raven, R., & Palgan, Y. V. (2019). Smart and sustainable cities? Pipedreams, practicalities and possibilities. *Local Environment, 24*(7), 557–564.

Foster, K. (2016). Geodesign parsed: Placing it within the rubric of recognized design theories. *Landscape and Urban Planning, 156*, 92–100 (Web).

Gahegan, M. (2020). Fourth paradigm GIScience? Prospects for automated discovery and explanation from data. *International Journal of Geographical Information Science, 34*(1), 1–21. https://doi.org/10.1080/13658816.2019.1652304

Geertman, S., Ferreira, J., Goodspeed, R., & Stillwell, J. (2015). *Planning support systems and smart cities*. Germany: Springer International Publishing.

Gleye. (2015). City planning versus urban planning: Resolving a profession's bifurcated heritage. *Journal of Planning Literature, 30*(1), 3–17. https://doi.org/10.1177/0885412214554088

Goodchild, M. F. (2007). Citizens as voluntary sensors: Spatial data infrastructure in the world of web 2.0. *International Journal of Spatial Data Infrastructures Research, 2*, 24–32.

Goodchild, M. F. (2019). Geography and GIScience: An evolving relationship. The. *Canadian Geographer, 63*(4), 530–539, 10.1111/cag.12554 [578].

Gordon, S. N., Murphy, P. J., Gallo, J. A., Huber, P., Hollander, A., Edwards, A., & Jankowski, P. (2021). People, projects, organizations, and products: Designing a knowledge graph to support multi-stakeholder environmental planning and design. *ISPRS International Journal of Geo-Information, 10*, 823. https://doi.org/10.3390/ijgi10120823

Greenfield, A. (2006). *Everyware: The dawning age of ubiquitous computing*. Boston: New Riders.

Haque, U. (2012). What is a city that it would Be 'smart. *City in a Box, 34*. https://haque.co.uk/papers/V34_page_140-142_Usman_Haque.pdf.

Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., Melo, G. de, Gutierrez, C., Gayo, J. E. L., Kirrane, S., Neumaier, S., Polleres, A., et al. (2020). *Knowledge graphs*. Available online: https://arxiv.org/abs/2003.02320.

Hollands, R. G. (2015). Critical interventions into the corporate smart city. Cambridge Journal of Regions. *Economy and Society, 8*(1), 61–77.

International GeoDesign Collaboration. (2020). https://www.igc-geodesign.org/. (Accessed 15 January 2022).

Jacobs, J. (1961). *The death and life of great American cities*. Vintage Books.

Janowicz, K., Gao, S., Grant, M. K., Hu, Y., & Bhaduri, B. (2020). GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *International Journal of Geographical Information Science, 34*(4), 625–636. https://doi.org/10.1080/13658816.2019.1684500

Jiang, H., Geertman, S., & Witte, P. (2020). *Smart urban governance: An alternative to technocratic "smartness"*. GeoJournal. https://doi.org/10.1007/s10708-020-10326-w

Karvonen, A., Cook, M., & Haarstad, H. (2020). Urban planning and the smart city: Projects, practices and politics. *Urban Planning, 5*(1), 65–68. https://doi.org/10.17645/UP.V5I1.2936

Karvonen, A., Cugurullo, F., & Caprotti, F. (Eds.). (2019). *Inside smart cities: Place, politics and urban innovation*. London: Routledge.

Keenan, P. B., & Jankowski, P. (2019). Spatial decision support systems: Three decades on. *Decision Support Systems, 116*, 64–76.

Kim, H. M., Sabri, S., & Kent, A. (2021). Smart cities as a platform for technological and social innovation in productivity, sustainability, and livability: A conceptual framework. *Smart Cities for Technological and social innovation. Case Stud. Curr. Trends Future Steps*, 9–28, 2021.

Kitchin, R. (2014a). The real-time city? Big data and smart urbanism. *Geojournal, 79.1*, 1–14 (Web).

Kitchin, R. (2014b). *The data revolution: Big data, open data, data Infrastructures and their consequences*. London: Sage.

Kitchin, R. (2021). Afterword: Decentering the smart city. In S. Flynn (Ed.), *Equality in the city: Imaginaries of the smart future*. Bristol: Intellect (in press).

Kitchin, R., Coletta, C., Evans, L., & Heaphy, L. (Eds.). (2019a). *Creating smart cities*. London: Routledge.

Kitchin, R., Graham, M., Mattern, S., & Shaw, J. (Eds.). (2019b). *How to run a city like amazon, and other fables*. Oxford: Meatspace Press.

Kitchin, R., Lauriault, T. P., & McArdle, G. (2014c). Knowing and governing cities through urban indicators, city benchmarking and real-time dashboards. *Regional Studies, Regional Science, 2*(1), 6–28.

Kitchin, R., Lauriault, T. P., & McArdle, G. (Eds.). (2017). *Data and the city*. London: Routledge.

Kuller, M., Reid, D., & Prodanovic, V. (2021). Are we planning blue-green infrastructure opportunistically or strategically? Insights from Sydney, Australia. *Blue-Green Systems, 3*(1), 255–268. https://doi.org/10.2166/bgs.2021.023

Lee, A., Mackenzie, A., Smith, G. J. D., & Box, P. (2020). Mapping platform urbanism: Charting the nuance of the platform pivot. *Urban Planning, 8*(1), 116–128.

Lefebvre, H. (1991). *The production of space*. Blackwell.

Li, W. (2020). GeoAI: Where machine learning and big data converge in GIScience. *Journal of Spatial Information Science, 20*, 71–77. https://doi.org/10.5311/JOSIS.2020.20.658

Li, W., Batty, M., & Goodchild, M. F. (2020). Real-time GIS for smart cities. *International Journal of Geographical Information Science, 34*(2), 311–324. https://doi.org/10.1080/13658816.2019.1673397

Lord, S., Frémond, M., Bilgin, R., & Gerber, P. (2015). Growth modelling and the management of urban sprawl: Questioning the performance of sustainable planning policies. *Planning Theory & Practice, 16*(3), 385–406. https://doi.org/10.1080/14649357.2015.1061140

Malczewski, J., & Rinner, C. (2015). *Multicriteria decision analysis in geographic information science*. New York: Springer.

Mirzabeigi, S., & Razkenari, M. (2022). Design optimization of urban typologies: A framework for evaluating building energy performance and outdoor thermal comfort. *Sustainable Cities and Society, 76*, Article 103515. https://doi.org/10.1016/j.scs.2021.103515

Morgan, K., & Webb, B. (2020). Googling the city: In search of the public interest on Toronto's 'smart' waterfront. *Urban Planning, 8*(1), 84–95.

Mu, W., & Tong, D. (2020). On solving large p-median problems. *Environment and Planning B: Urban Analytics and City Science, 47*(6), 981–996.

Pavlovskaya, M. (2018a). Theorizing with GIS: A tool for critical geographies? *Environment & Planning A, 38*, 2003–2020. https://doi.org/10.1068/a37326

Pavlovskaya, M. (2018b). Critical GIS as a tool for social transformation. *Canadian Geographer/Le Géographe Canadien, 62*, 40–54.

Pearman, O., & Cravens, A. E. (2022). Institutional barriers to actionable science: Perspectives from decision support tool creators. *Environmental Science & Policy, 128*, 317–325. https://doi.org/10.1016/j.envsci.2021.12.004

Pickles, J. (Ed.). (1994). *Ground Truth: The social implications of geographic information systems*. New York: The Guilford Press.

Rathore, M., Mazhar, et al. (2016). Urban planning and building smart cities based on the internet of Things using big data analytics. *Computer networks (Amsterdam, Netherlands: 1999, 101*, 63–80 (Web).

Razavi, S. (2021). Deep learning, explained: Fundamentals, explainability, and bridgeability to process-based modelling. *Environmental Modelling & Software, 144*, Article 105159. https://doi.org/10.1016/j.envsoft.2021.105159

Rivard, K., & Cogswell, D. (2004). Are you drowning in bi reports? Using analytical dashboards to cut through the clutter. *Information Management, 14*(4), 26.

Sadowski, J. (2019). A digital deal for the smart city: Participation, protection, progress. In C. Coletta, L. Evans, L. Heaphy, & R. Kitchin (Eds.), *Creating smart cities* (pp. 21–32). New York: Routledge.

Santamouris, M. (2013). Using cool pavements as a mitigation strategy to fight urban heat island—a review of the actual developments. *Renewable and Sustainable Energy Reviews, 26*, 224–240 (Web).

Silva, B. N., Khan, M., Jung, C., Seo, J., Muhammad, D., Han, J., Yoon, Y., & Han, K. (2018). Urban planning and smart city decision management empowered by real-time data processing using big data analytics. *Sensors, 18*(9), 2994. https://doi.org/10.3390/s18092994

Stefanidis, A., Crooks, A., & Radzikowski, J. (2013). Harvesting ambient geospatial information from social media feeds. *Geojournal, 78*(2), 319–338. https://doi.org/10.1007/s10708-011-9438-2

Steinitz, C. (2012). *A framework for geodsign: Changing geography by design*. ESRI Press.

Sun, Y., & Li, S. (2016). Real-time collaborative GIS: A technological review. *ISPRS Journal of Photogrammetry and Remote Sensing, 115*, 143–152 (Web).
The U.S. Environmental Protection Agency. (2021). "What is green infrastructure?". https://www.epa.gov/green-infrastructure/what-green-infrastructure. Date of Access: 01-16-2022. (Accessed 16 January 2022).
Tong, D., & Murray, A. (2012). Spatial optimization in geography. *Annals of the Association of American Geographers, 102*(6), 1290–1309.
Torabi Moghadam, S., & Lombardi, P. (2019). *An interactive multi-criteria spatial decision support system for energy retrofitting of building stocks using CommuntiyVIZ to support urban energy planning* (Vol. 163). Building and Environment, Article 106233.
Torabi Moghadam, S., Lombardi, P., et al. (2018). A new clustering and visualization method to evaluate urban heat energy planning scenarios. *Cities, 88*, 19–36. https://doi.org/10.1016/j.cities.2018.12.007
Uran, O., & Janssen, R. (2003). Why are spatial decision support systems not used? Some experiences from The Netherlands. *Computers, Environment and Urban Systems, 27*(5), 511–526. https://doi.org/10.1016/S0198-9715(02)00064-9
Van Schrojenstein Lantman, J., Verburg, P. H., Bregt, A., & Geertman, S. (2011). Core principles and concepts in land-use modelling: A literature review. In E. Koomen, & J. Borsboom-van Beurden (Eds.), *Land-use modelling in planning practice. GeoJournal library* (Vol. 101). Dordrecht: Springer. https://doi.org/10.1007/978-94-007-1822-7_3.
Wyatt, R. (2004). The great divide: Differences in design style between architects and urban planners. *Journal of Architectural and Planning Research, 21*(4), 38–54.
Yao, J., Zhang, X., & Murray, A. T. (2018). Spatial optimization for land-use allocation: Accounting for sustainability concerns. *International Regional Science Review, 41*(6), 579–600. https://doi.org/10.1177/0160017617728551
Yigitcanlar, T., Kamruzzaman, M., Buys, L., Ioppolo, G., Sabatini-Marques, J., da Costa, E. M., & Yun, J. J. (2018). Understanding "smart cities": Intertwining development drivers with desired outcomes in a multidimensional framework. *Cities, 81*, 145–160. https://doi.org/10.1016/j.cities.2018.04.003
Yin, L., Chen, J., Zhang, H., Yang, Z., Wan, Q., Ning, L., Hu, J., & Yu, Q. (2020). Improving emergency evacuation planning with mobile phone location data. *Environment and Planning B: Urban Analytics and City Science, 47*(6), 964–980. https://doi.org/10.1177/2399808319874805
Yin, C. T., Xiong, Z., Chen, H., Wang, J., Cooper, D., & David, B. (2015). A literature survey on smart cities. *Science China Information Sciences, 58*(10), 1–18. https://doi.org/10.1007/s11432-015-5397-4
Zerger, A., & Ingle Smith, D. (2003). Impediments to using GIS for real-time disaster decision support. *Computers, Environment and Urban Systems, 27*(2), 123–141 (Web).
Zhang, Y., Murray, A. T., & L Turner, B. (2017). Optimizing green space locations to reduce daytime and nighttime urban heat island effects in Phoenix, Arizona. *Landscape and Urban Planning, 165*, 162–171 (Web).
Zhou, H., He, S., et al. (2019). Social inequalities in neighborhood visual walkability: Using street view imagery and deep learning technologies to facilitate healthy city planning. *Sustainable Cities and Society, 50*, Article 101605. ISSN 2210-6707.
Zou, Z., Cai, T., & Cao, K. (2020). An urban big data-based air quality index prediction: A case study of routes planning for outdoor activities in beijing. *Environment and Planning B:Urban Analytics and City Science, 47*(6), 948–963. https://doi.org/10.1177/2399808319862292