Transforming Smart Cities with Spatial Computing

Yiqun Xie, Jayant Gupta, Yan Li, Shashi Shekhar
Department of Computer Science and Engineering University of Minnesota, Twin Cities
Email: xiexx347, gupta423, lixx4266, shekhar@umn.edu

***Abstract*—Spatial methods have a rich history of reforming city infrastructure. For example, John Snow's 1854 London Cholera map spurred cities to protect drinking water via sewer systems and to increase green spaces for public health. Today, geospatial data and mapping are among the technologies that cities use the most due to strategic (e.g., long-term planning, land-use), tactical (e.g., property tax, site selection, asset tracking) and operational (e.g., E-911, situation awareness, gunshot location) use cases. Moreover, they (e.g., Google Maps) help citizens navigate, drones stay clear of restricted spaces (e.g., airports, NFL games), and sharing-economy (e.g., Uber) match consumers with nearby providers. Future spatial computing opportunities for smart cities are even more compelling. GIS promises to help re-imagine, redesign, see, and compare alternative infrastructure futures to address risks (e.g., climate change, rising inequality, population growth) and opportunities (e.g., autonomous vehicles, distributed energy production). This paper surveys recent spatial computing accomplishments and identifies research needs for smart-city use-cases.**

***Index Terms*—spatial computing, smart city, infrastructure**

I. Introduction

The next 30 years will see the world's urban population grow by 2.5 billion [1]. The increased population will mean the addition of much new infrastructure (mainly in Asia and Africa) and the repair of existing infrastructure worldwide [2]. Adding to these challenges will be the impact on cities of global climate change (e.g., sea level rise in coastal areas). Meanwhile, there are new possibilities on the horizon like autonomous vehicles and solar energy generation. The need for new infrastructure provides a unique opportunity for citizens, engineers, scientists and governments to come together and build 'smart cities' that promote health and well-being, equity, and sustainability [3]. The vision aligns with the United Nations' 17 goals for ensuring sustainable food, energy, and water systems; access to education; and other benefits of healthy sustainable communities in the future [4].

Infrastructure generally refers to the physical and organizational structure that is required for the operation of a society. Table I lists multiple infrastructure and marks (✓) their importance in three perspectives. Core infrastructure includes transportation, food, energy, water, public health, waste and sanitation, and buildings. Ramaswami et al. [3] consider green spaces infrastructure. IEEE, in its 2018 international conference on smart-cities took an inter-city perspective and recognized a number of other key sectors such as information technology (e.g., communication technology) and defense [5].

TABLE I: Smart City Infrastructure

Infrastructure Type	Ramaswami [3]	IEEE SCC [5]	PPD-21 [6]
Transportation, Mobility	✓	✓	✓
Food & Agriculture	✓	✓	✓
Energy	✓	✓	✓
Water	✓	✓	✓
Health-care, public health	✓	✓	✓
Waste and sanitation	✓	✓	✓
Buildings	✓	✓	
Green/public spaces	✓		
Defense Industry		✓	✓
Emergency Services			✓
Financial		✓	✓
Government		✓	✓
Information Technology		✓	✓
Education sector		✓	
Law, Privacy		✓	
Nuclear			✓
Chemical sector			✓
Commercial sector			✓
Private sector			✓
Manufacturing sector			✓
Dams			✓
Spatial Technology (maps, positioning, GIS)			

At the national level, presidential policy directive 21 (PPD-21) [6] issued under President Obama lists 16 critical sectors and 14 of them depend on GPS [7].

Spatial methods have often governed the transformation of cities. For example, John Snow's 1854 cholera map led to the creation of sewer system, increasing green space, and urban planning [8]. The changes occurred due to his map linking cholera to drinking water contamination during the 1854 Broad Street cholera outbreak in London. Figure 1 shows the map Snow drew of the cholera cases mostly located around water pumps. Similarly, cities today employ spatial methods for improved governance. Geospatial data and mapping technologies are used extensively for strategic (e.g., long-term planning, land-use), tactical (e.g., property tax, site selection, asset tracking), and operational (e.g., E-911, situation awareness, gunshot location) use-cases by city administrations.

Traditional urban infrastructure systems that incorporate modern Information and Communication Technologies (ICT) can help to achieve the vision of 'smart city' [9]. Since a key feature of all city infrastructure namely, transportation networks, housing, energy, and utility systems is its spatial nature [10]. It is important to use computing techniques that can handle special properties of spatial data, such as heterogeneity and auto-correlation [11]. Such techniques come under the purview of spatial computing. Formally, spatial computing refers to the ideas, tools, solutions, technologies

978-1-5386-5959-5/18/$31.00 ©2018 IEEE

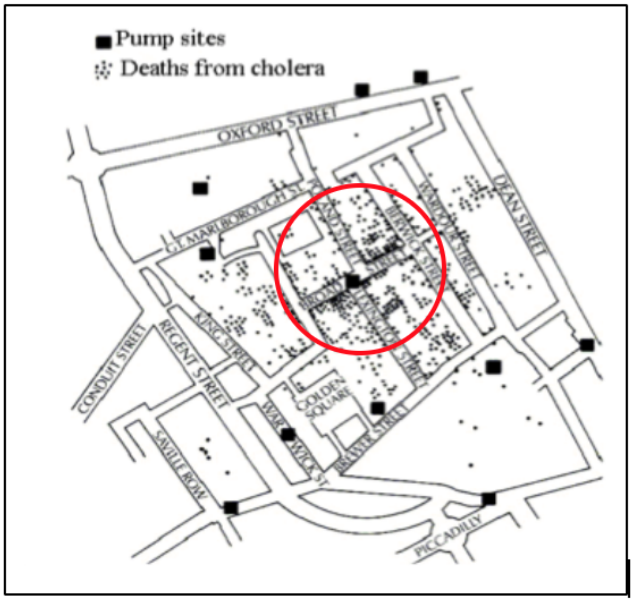


Fig. 1: Map by John Snow where hotspots of cholera cases can be seen around the pump site(s).

and systems that are used to analyze data with geographic information [12].

Outline: The rest of the paper is organized as follows: In section 2 we provide a brief overview with limitations of related work, our contribution and scope of this paper. Section 3 and Section 4 describe the accomplishments and research needs of five broad areas of spatial computing respectively. Section 5 concludes the paper with a look to future work.

II. Related Work and Our Contributions

Batty et al. [9] provides a vision for smart-cities to enhance economy, and governance. are enhanced. Yin et al. [13] discuss developing country challenges such as, air quality and clean water. Shelton et al. [14] explore the effect of new technological developments and the data-driven approach on the administration (e.g., urban policy) in Louisville and Philadelphia. Mohanty [15] surveys the internet of things and cyber physical challenges in smart-cities.

Angelidou [16] reviews multiple factors that affect policy making for the development of smart-cities. For example, national versus local strategies differ due to geographical scale, strategies for new versus existing cities differ due to reuse, demolition or repair of old infrastructure and technologies. Zheng [17] examines urban computing (data management and analytics) issues related to transportation, environment, etc. Gruen [18] discusses the need for high-fidelity spatial data, e.g., digital topographic models and 3D building models.

Limitations of related work: Table II lists the most widely adopted technologies in U.S. cities over recent years (2015-2017). It shows that geospatial and mapping technologies are widely used. For example, all sectors of modern life, from transportation to finance, depend on GPS. GPS is also responsible for timing our clocks, tracking our rides, important packages and airlines [7]. As shown in Figure 2 most of the

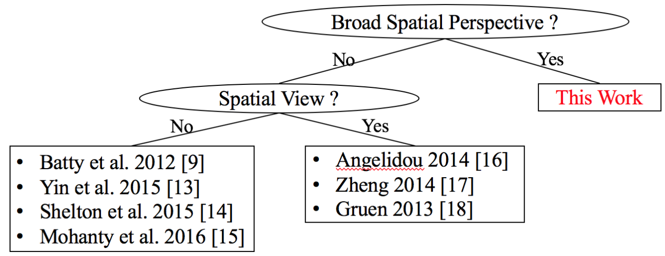


Fig. 2: Related Work

prior work [9], [13]–[15] does not provide a spatial perspective. Further, the related work [16]–[18] that has a spatial view is narrowly focused on few data-types such as trajectories or imagery. Spatial infrastructure (e.g., maps, positioning, GIS, etc) is also missing from prior lists of city infrastructure as shown in the last row of Table I.

TABLE II: Most widely adopted technologies city-wide

Rank	2015 [19]	2016 [20]	2017 [21]
1	**(69%) Geospatial / Mapping**	(93%) Public Meeting records	**(53%) GeoSpatial / Mapping**
2	(67%) Virtualization	(92%) Wireless Infrastructure	(48%) Cybersecurity
3	(60%) Performance Benchmarks	(91%) Redundant/ Offsite Data Storage	(34%) Predictive Policing
4	(58%) Transaction Processing	(90%) Endpoint Security	(32%) eDiscovery
5	(57%) Project Management	(85%) Broadband Infrastructure	(20%) Predictive Analytics

Our Contributions: We consider five broad spatial computing areas: (1) positioning, (2) remote sensing, (3) spatial data science, (4) spatial database and management systems, and (5) geographic information system (GIS) and cartography. Positioning and remote sensing relate to the generation and collection of geographic data. Spatial data science studies analysis techniques for geographic data. Spatial database management systems provide efficient storage and optimal querying of data. Finally, GIS and cartography represent the integrated platform where all of these areas are used to develop useful applications. For each of the five areas, we list concrete examples of current accomplishments and future research needs of spatial computing to achieve various smart city infrastructure goals.

Scope: The paper does not address social science topics (e.g., inequality), engineering topics (e.g., managing rainwater to reduce flood or ground sagging), etc. In addition, the paper does not aim at exhaustive survey of spatial computing use-cases as they may vary across cities.

III. Accomplishments

This section describes the key accomplishments in each of the five broad areas of spatial computing. The accomplishments have found importance in multiple domains such as, public saefty, urban heat detection, air pollution, routing services, and city planning among others.

A. Positioning: Positioning determines geographic coordinate values in real-time. Global Navigation Satellite Systems (GNSS) [22] (e.g., Global Positioning System or GPS [23]) are usually used for outdoor positioning. GPS is also used to measure time and synchronize millions of computers on Earth [24]. Further, outdoor positioning is used in cellular devices enabling mapping and ride-hailing services. Financial (e.g., time-stamping transactions), defense (e.g., conduct military operations), and transportation (e.g., vehicle tracking) sectors depend on GPS for their day-to-day functioning. There are around 2 billion GPS devices in use today and that number is expected to increase to 7 billion by 2022.

Determination of position within closed spaces is called indoor positioning, and is usually accomplished using RFID and Wi-Fi based methods [25]. Indoor positioning is primarily used in hospitals, retail sectors, large warehouses or factories, and it is increasingly available for efficient navigation inside airports, or large shopping complexes [26]. Both indoor and outdoor positioning has been used to build navigation systems for blind [27].

Beyond GPS positioning systems help public safety; for example, sound sensors on utility poles can be used for real-time location of a gunshot [28]. Noise source positioning [29], [30] are useful for monitoring noise pollution in a city or around sensitive areas such as hospitals. There are also techniques [31] that use trajectory data to to determine avoidance regions for early detection of urban decay.

B. Remote Sensing: Unlike traditional time and resource consuming manual land surveys, remote sensing technology continuously monitors the earth, including urban areas, using advanced sensor platforms (e.g., satellites, aircrafts, unmanned aerial vehicles). The versatility of these sensors allows the collection of spectral (e.g., both visible and non-visible) and elevation data. Remote sensing data is valuable in smart city monitoring, management, planning, and can help monitor infrastructures such as buildings, energy, green spaces, etc.

High-resolution (e.g., 1 meter) aerial imagery and LiDAR datasets (i.e., sources of topographical models) have been made available (e.g., National Agriculture Imagery Program [32], Minnesota LiDAR repository [33]), and support general land-use classification (e.g., built areas, green space, water, roads) based on machine learning and, more recently, deep learning techniques [34], [35]. Rule-based data mining techniques have also been applied on LiDAR data to classify different types of infrastructure at city or state scales [36] as shown in Fig. 3(b). Such classification helps decision-making in city management and planning. For example, a classification map can be used to evaluate residents' access to green spaces (e.g., park) at different city locations and allocate new tree resources to regions with lower accessibility, thus helping smart cities meet well-being and equity goals.

Remote sensing research has also explored the detection and analysis of urban heat islands and urban sprawl [37], [38], which aims to improve the sustainability of city development. In addition, LiDAR data has been used to facilitate the use of renewable solar energy in smart cities (Fig. 3(c)). The high-resolution elevation information allows identification of flood risks, estimation of drinking water quantity, physics-based simulation methods to estimate the seasonal or annual

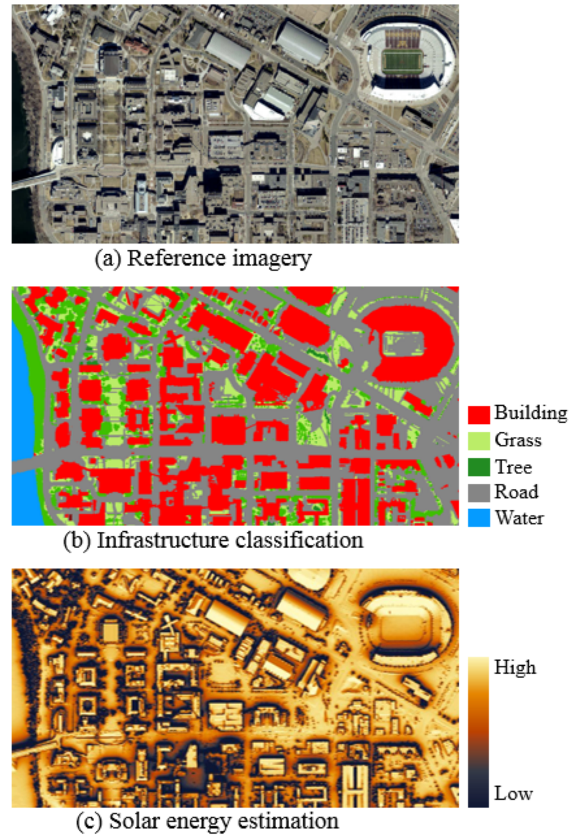


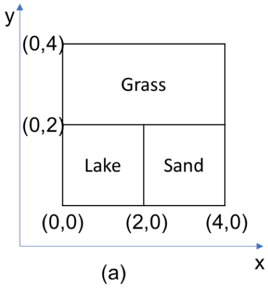
Fig. 3: Example remote sensing use cases in smart cities. (Best in color)

energy generated by sunlight (e.g., determined by sun angle, climate, obstacle, etc.) at specific locations (e.g., roof of a household) [39]–[41].

C. Spatial Data Science: John Snow's Cholera map (1) illustrates the power of spatial data science [42] in detecting useful, interesting, novel, and non-trivial patterns such as hotspots. Spacial data science generalize traditional statistics, data mining, and machine learning to deal with spatial auto-correlation, heterogeneity and other geographic challenges.

It has been applied to a variety of infrastructures (e.g., transportation, sanitation, and security) in smart cities. Specifically, urban hotspot detection, which finds geographic regions with statistically high concentration of certain events, helps (1) alert public health officials to outbreaks of disease (e.g., flu outbreaks) [43], [44]; (2) police locate serial criminals [45]; (3) cities identify roads that are in poor condition or lack necessary safety infrastructure [46]; etc. Co-occurence pattern detection can be used in transportation and energy sectors to discover highly correlated associations between certain vehicle behaviors (e.g., braking) and high combustion or energy cost [47]. Spatial outlier detection has also been used to find anomalies in river water flow and to send pollution and contamination warnings [48]. Spatial machine learning has played an important role in city security surveillance (e.g., face matching [49], license plate reading [50]), land-use classification and monitoring [35], [51], travel-time prediction [52], etc.

D. Spatial Database Management Systems: A database



(a)

ID	Land Cover	Area/Boundary
1	Grass	[(0,2),(4,2),(4,4),(0,4)]
2	Lake	[(0,0),(2,0),(2,2),(0,2)]
3	Sand	[(2,0),(4,0),(4,2),(2,2)]

(b) Object-base model

$$f(x,y) = \begin{cases} Grass, 2 \le x \le 4, 2 < y \le 4 \\ Lake, 0 \le x \le 2, 0 \le y \le 2 \\ Sand, 2 < x \le 4, 0 \le y \le 2 \end{cases}$$

(c) Field-based model

Fig. 4: Example data model in SDBMS.

management system (DBMS) is a computerized system for defining, creating, querying, updating, and managing a database. A traditional DBMS provides persistence across failures; concurrency control, which allows different parts of a transaction to be executed out-of-order without affecting the final outcome; and scalability to search queries on very large datasets which do not fit inside main memories of computers. While a traditional DBMS is efficient for non-spatial queries, such as listing the names of all roads, it is not efficient for spatial queries, like listing the name of all roads within one kilometer of a building. In order to facilitate the use of spatial data (e.g., aerial imagery), we need Spatial DBMS.

A Spatial DBMS is a software module that can work with an underlying DBMS. It supports spatial data models, spatial abstract data types (ADTs), and a query language from which these ADTs are callable. It also supports spatial indexing, efficient algorithms for processing spatial operations, and domain specific rules for query optimization.

Two commonly used spatial data models are field-based and object-based models. Figure 4(a) shows an example of the spatial data of a park. An object-based model represents the information with three polygons (Figure 4(b)); a field-based model represents the information as a mapping from a spatial framework (a partition of space) to an attribute domain (e.g., land cover) (Figure 4(c)). Each object in an object-based model is a distinct identifiable thing relevant to an application, which has spatial and non-spatial attributes as well as operations. Spatial attributes of objects can be represented as points, lines, polygons, as well as collections of them. Operations on spatial objects in an object-based model generally can be classified into four groups as shown in Table III, namely, set-based, topological, directional, and metric operations. Operations for field-based models are of three types: local, focal, and zonal. The value of a local operation's result at a given location depends only on the value of the input field at the location (e.g. thresholding), while that of a focal operation depends on a small neighborhood around the location (e.g. gradient). Zonal operations are naturally associated with aggregate functions. Their results at a location are determined by a zone.

TABLE III: Classifying Operations in Object-based Models

Operation Class	Examples
Set-based	Union, Intersection, Contain, Within,...
Topological	Touch, Disjoint, Overlap, ...
Directional	South, Northeast, ...
Metric	500 miles away, ...

Spatial databases are becoming increasingly accessible nowadays. Example include US land-parcel database with 150 million parcels, census, remote sensing images (in Google Earth Engine or Amazon web-services Earth [53], Seattle Online Crime Maps [54], Chicago Crime Map [55]), metro transit (e.g. Chicago Transit Trackers [56]), apartments (e.g. Apartments.com), roads (e.g. Google Maps), etc. Spatial DBMS applications are ubiquitous in smart cities. Waze, a software providing turn-by-turn navigation based on a road map, user-submitted travel times, and route details, is a good example of a Spatial DBMS [57]. Spatial DBMS is also utilized to hold locations of all underground infrastructure (e.g., water mains, gas lines, telephone wires, broadband) for use cases from public safety (e.g., before digging to reduce collateral damage) to proactive maintenance of all co-located infrastructure types at a site to reduce repeated digging at a site. Other applications of Spatial DBMS include E911 which was introduced to provide the location of callers to 911 operators [58], as well as enforcing restricted zones such as airports for Unmanned Aerial Vehicles [59].

E. GIS/Cartography: A geographic information system (GIS) is an integrated platform to collect, manage, analyze and visualize spatio-temporal information. As shown in Table II, GIS has been widely used in smart-city projects for urban planning, development, and management. In India, smart cities will have command & control centers that will utilize a GPS equipped ecosystem (e.g.,trash bins, vehicles, streets, poles etc.) to monitor and manage resources [60]. Japan has also been using GIS to help with city master planning, regulation revision and city planning ordinance revision [61]. In order to improve the functionality of GIS, research has been conducted on generating maps and their annotation [62], map-matching spatial data to existing maps [63], and evacuation planning that considers the capacity of spatial networks [64].

IV. Research Needs

This section describes the research needs in each of the five broad areas of spatial computing. These needs have emerged from existing challenges such as GPS jamming and spoofing attack, or need for advancement in existing technologies such as aerial imagery. Furthermore, spatial data has unique properties that require attention when devising algorithms and methods for their analysis. Finally, with the increased use of spatial technologies, application driven requirements (e.g., routing services) have emerged that needs to be addressed.

A. Positioning: Reverse E911 automatically provides the location of a caller to a dispatcher; however, it cannot provide vertical position or altitude. This shortcoming can become a major hindrance to determining the accurate location of callers from high rise buildings. Further, positional knowledge of various infrastructure interdependence is necessary for improved resilience of city infrastructure to man-made disasters (e.g., construction work rupturing nearby gas pipelines) and emergencies. Furthermore, high-fidelity maps with road furniture information and accurate positioning can help to improve the accuracy of self-driving cars. However, it is important that the position of marked objects be verified manually.

GPS is used for positioning as well as time service by two Billion GPS receivers in smart phone, vehicles, computers, sensors, etc. across all critical infrastructures listed in Table I. Thus, GPS disruption by jamming or spoofing or satellite failures can massively disrupt our civilization by disrupting cell-phones, ATMs, sharing-economy (e.g., uber), Amazon delivery, etc. Unfortunately, it is trivial to jam GPS by purchasing widely available and cheap devices and tens of thousands of attacks have occurred in transportation sector from airports to trucks to ride-sharing services. In addition, adversaries have exhibited capability to destroy satellites. This calls for steps to improve the existing satellite systems to increase the signal strength and create positioning backup systems [65] such as Enhanced Long Range Navigation (eLORAN). The integrity of GPS needs to be strengthened through modernization, "survivability" (e.g., through redundancy), setting of manufacturing standards, and understanding of resiliency against multiple hazards [66].

Outdoor positioning based on GPS needs further research to understand space weather and its effects on signal delay and accuracy. There is a need for broader coverage and improved observation of ionospheric and atmospheric parameters. Further, the development of space and weather products should take into account user requirements (e.g., terms of accuracy, availability and integrity).

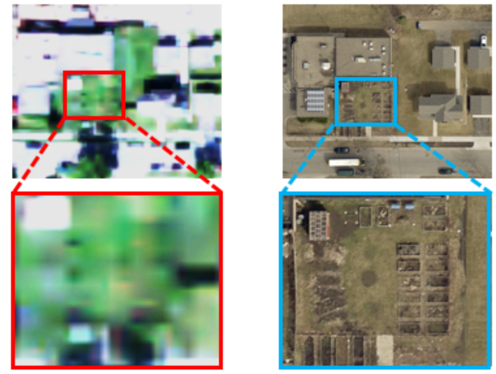
B. Remote Sensing: Remote sensing presents new challenges and research opportunities in smart city infrastructure management. One key challenge is generating inventories of objects in a city at a fine-scale (e.g., individual trees and their species as part of green infrastructure), which require object detection techniques. Recent advances in deep learning have shown promising results in recognizing objects in everyday images [67], [68] as well as improved ability to construct features for remote sensing data [69]. While deep learning is a potentially powerful tool for detecting objects in remote sensing imagery, we still need the unique signatures of different object classes that distinguish one class from another. However, in many critical smart city applications, such signatures remain unclear.

In the last decade the invasive species Emerald Ash Borer has spread to many countries and killed millions of ash trees, posing a severe threat to green infrastructure in northern cities. In Europe, the ash tree has been predicted to face extinction [70], and in the US, the cost for curing or removing all ash trees has been estimated to be over 10 billion US dollars [71]. To respond to this and potentially similar threats for other species, (e.g., Oak Wilt, Mountain Pine beetle), many cities have decided to create inventories of individual trees (e.g., location, size, species). However, the current resolution of satellite imagery is typically not sufficiently high to provide distinct signatures of different tree species from an aerial view.

Fig. 5 shows an example of a 1-meter resolution satellite imagery and four tree canopies, where the blue circles represent elm trees and red circles represent ash. In the visual

(a) Reference imagery (b) Individual tree examples

Fig. 5: Trees in remote sensing imagery (1m resolution). (Best in color)



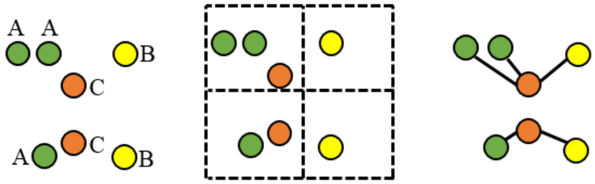
(a) Resolution: 1m (b) Resolution: 7cm

Fig. 6: Urban garden in 1m and 7cm resolution imagery. (Best in color)

bands of the images, the canopies from the two different genus share mostly the same color and texture, making it difficult to separate them into distinct classes. On the other hand, related research has demonstrated that detailed leaf shapes and textures in higher resolution aerial imagery can be used to construct unique signatures of tree species using deep learning models [72]. Hyper-spectral imagery has also demonstrated usefulness in tree species classification [73]. This motivates collection of very high resolution (e.g., 7cm, hyperspectral) remote sensing data in spatial or spectral dimensions at large scales. Besides green infrastructure, improved high-resolution imagery also offers new opportunities to detect other interesting infrastructure objects such as urban gardens (Fig. 6). Availability of night time thermal imagery can help determine poorly insulated buildings.

C. Spatial Data Science: As the popularity of data science (e.g., data mining, statistics, machine learning) increases, more and more emphasis is being placed on a transdisciplinary view of data science techniques to improve the interpretability and robustness of results [42], [74]. This is particularly important for smart city applications due to the high cost (e.g., stigmatization, economic & political cost) of false positives (e.g., spurious disease outbreak warnings) and inaccurate classification and prediction (e.g., causing autonomous driving accidents, wrong flu peak estimation). Research challenges include space partitioning impact on statistics, real-time, fairness, etc.

Statistics and space partitioning: In data science, samples are usually assumed to follow an i.i.d. (identically and independently distributed) distribution, which is the foundation of many techniques (e.g., linear regression, decision trees, random forest, neural network). However, this i.i.d. assumption is not valid for geospatial data, which are often spatially auto-correlated [42]. Direct application of i.i.d. based methods on spatial data can lead to salt-and-pepper errors or fragmented



(a) Point distribution (b) Space partitioning (c) Neighbor graph

Fig. 7: Effect of space partitioning on statistics. (Best in color)

results [75], [76]. In addition, breaking up the spatial dependence between samples may lead to opposite statistical conclusions from the true phenomenon.

Fig. 7(a) shows an example distribution of two diseases A and B and a potential cause C in a spatial domain. In order to apply traditional statistical measures to evaluate the correlation between the disease and the cause, a typical preprocessing step is to break the space into a few partitions such as counties, or census blocks (Fig. 7(b)) and examine how frequently the diseases and the cause appear together in each partition using i.i.d. based measures (e.g., Pearson's correlation coefficient) [42]. With this space partitioning, the distribution vector v of a disease or cause x can be constructed as $v(i) = \text{count(instances of } x \text{ inside } i^{th} \text{ partition)}$, where i is the ID of a partition. For example, the distribution vector of disease A is $[2, 0, 1, 0]$.

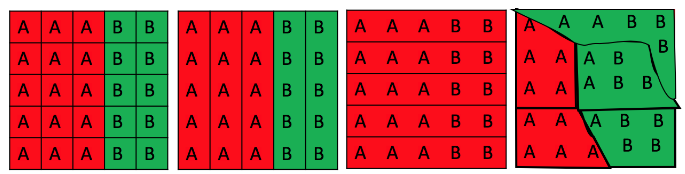
Table IV shows the Pearson's correlation coefficients computed using the vectors, where the negative value "-1" for disease B and cause C means that B and C are completely repulsive in the spatial domain. However, looking at the point distribution, we can see that the locations of both disease A and B tend to appear near the locations of C, which indicates that both diseases are spatially correlated with C. Since such adjacency was broken by the space partitioning, a direct use of Pearson's correlation coefficient led to the opposite conclusion. Similar errors are exhibited by support measure used by association rule in data mining. With a spatial neighbor graph (Fig. 7(c)) [42], such spatial relationship can be maintained, so we can reach correct conclusions as shown by the high participation index [77] values (range $[0, 1]$) in Table IV, where both values are 1 meaning both diseases are spatially colocated. Ripley's cross-K may help as well.

TABLE IV: Pearsons correlation coefficient, participation index, and Support for disease and cause pairs

Disease & cause	Pearsons Corr. Coefficient	Ripley's cross-K	Participation Index	Support
(A,C)	0.9	0.5	1.0	0.5
(B,C)	-1.0	0.5	1.0	0

This example shows that traditional statistical measures and approaches (e.g., machine learning) based on the i.i.d. assumption are inadequate for spatial data. Arbitrary space partitioning should not be directly used to transform spatial samples into i.i.d. samples. Sometimes in human environments, however, space partitioning is unavoidable (e.g., political district zoning). This leads to a well-known phenomenon called the "Modifiable Areal Unit Problem" (MAUP) [78], also referred to as the aggregation effect. Formally, the problem states that the output of aggregate measures depends on the size and shape of the partition or modifiable area units. Therefore, the analysis or findings may differ as the partitioning change.

Gerrymandering, one of the most popular examples of MAUP [79], is when a political party boosts the chance of winning in an election by manipulating the boundaries of electoral constituencies. Figure 8 shows an example of how space partitioning can affect the calculation of majority measurement. Figure 8(a) shows input data with 15 A and 10 B votes shown by red and green respectively. Vertical(Figure 8(b)) and Horizontal(Figure 8(c)) partitioning results in A winning a majority of the partitions, 3 and 5 respectively. However, partitioning where B can win despite overall minority status is shown in Figure 8(d). Gerrymandering threatens citizens' sense of fairness in political elections. A MAUP problem is typically handled by using a point dataset. However, when point datasets are not available, policies (e.g., formation of electoral districts) and conclusions (e.g., poverty stricken areas [80]) should be made conditional to the underlying spatial partitioning.



(a) Input Data (b) 3A – 2B (c) 5A – 0B (d) 2A – 3B

Fig. 8: Modifiable Areal Unit Problem, e.g., gerrymandering. (Best in color)

Real-time: Determination of emerging spatial patterns in real-time can be useful for critical infrastructure protection [81]. Real-time spatial patterns can aid in assessing and reducing damage to infrastructure and improving city resiliency. For example, emerging circular hotspots [82] have been designed to detect outbreaks of disease and crime and help contain cases of disease outbreak. Computationally, finding spatial patterns in real-time is costly due to the high volume, velocity, and variety of data. However, techniques such as parallel processing [83] and incremental algorithms can be used to reduce computational cost.

Fairness: As data science techniques continue to improve the efficiency and quality of people's lives, fairness of results is gradually becoming a critical concern [84]. Given that equity is an important smart city goal [3], spatial data science methods should also consider potential fairness aspects during algorithm design. For example, in a ride sharing system, while it is important for algorithms to quickly match consumers and drivers and try to minimize the commute time, it is also important to address the fairness among individual consumers (e.g., in a pool scenario) [85]. Service providers should also be considered in the decision making [86]. To fulfill the equity goal in smart cities, algorithmic fairness should be given more attention in future research.

D. Spatial Database Management Systems: New research is necessary in order for Spatial DBMS to handle emerging societal needs. Due to the pervasive use of location aware smartphones, it is easy for companies to keep track and record users' location and time. For example, this data can be easily analysed to know an individual's work and home locations.

Therefore, research needs to devise policies (e.g., EU General Data Protection Regulation [87]), laws and norms that balance the needs of national security, businesses and civil society.

Another active research area is route selection. Effort has been made to estimate time of arrival based on historical travel data and road maps [88], [89]. However, smaller time cost does not necessarily mean smaller energy consumption. The time cost of a vehicle traveling along a route is determined by the route's length and the vehicle's average speed, the vehicle's energy consumption is also affected by geographic factors like weather, terrain, road angle/layout and intersection properties, as well as the vehicle's kinetic intensity and weight. Therefore, energy consumption should be treated differently than time cost. Meanwhile, the energy consumption of traveling along two adjacent road segments is not independent, so the method of estimating the energy consumption of each road segment separately and then summing up the energy consumption of the road segments along the route to find the route's energy consumption is inaccurate. The traditional routing methods from graph theory (e.g., Dijkstra's, A*) which treat the cost of each road segment independently need to be adjusted for dependency between adjacent row segments.

Order-dispatch matching —pairing service providers and customers such that criteria on travel distance and waiting time are met —is an important problem in the sharing economy. Research is needed to satisfy many conflicting requirements for the broker (e.g. keeping the system alive), customers (e.g. minimizing travel distance and waiting time), and service providers (e.g. maximizing revenue). A study [90] was conducted to match service providers and consumers in a fair manner.

E. GIS/Cartography: While most current work in GIS and cartography focuses on outdoor spaces, within a smart city context, indoor space is also important for a variety of applications, including indoor navigation, building evacuation and rescue during emergencies (e.g., fire), energy and waste management, anomaly detection (e.g., sensors), etc. To utilize spatial computing indoors, the collection and integration of indoor spatial data needs to be improved. Several spatial data standards have been established. For example, CityGML [91] and IndoorGML [92] (GML stands for Geography Markup Language) include standardized data models and exchange formats for indoor spatial data.

While these standards define general spatial data models (e.g., visualization, navigation), they have limited applications for many critical smart city infrastructures, such as energy, the Building Information Model (BIM) [93] (e.g., for fire safety) is another indoor standard widely used in the engineering field, which covers a broader set of building information (e.g., energy) [94] that is closely related to smart city infrastructure. We envision that an integration of existing models (e.g., BIM, IndoorGML) will lead to a more complete and meaningful data model, one which can be easily used with spatial data science techniques (e.g., hotspot and anomaly analysis [45], [48], and optimization [76], [95]) to better assist decision-making in indoor environments.

Most indoor data has yet to be collected or converted to standard GIS formats. For example, detailed floor plans of many buildings may only be documented on paper or in AutoCAD formats. However, this information can be potentially converted to GIS data formats using rule-based methods or machine learning (e.g., deep learning). In addition, volunteered geographic information (VGI) can be utilized to improve indoor data collection for public properties. With the help of VGI, detailed information (e.g., visual texture, room type) may be added to enrich existing building datasets. With all potential benefits of growing the indoor data volume and quality, privacy concerns should always be considered and addressed carefully. For example, information on private properties should remain protected to its owners or authorized users, and some information may only be accessed by specific users (e.g., building manager). Access to building information can be controlled at multiple levels with the help of spatial database management systems detailed in the previous section.

V. Conclusions and Future work

Spatial computing is playing a vital role both in improving smart city infrastructure (e.g., transportation, building, green space) and achieving smart city goals (i.e., health and well being, equity, sustainability). Our discussion covered five broad areas within spatial computing, i.e., positioning, remote sensing, spatial data science, spatial database management systems and GIS/cartography. For each domain, we illustrated the use of related spatial computing techniques through their current accomplishments in smart city development, and then highlighted research needs to better solve challenging problems for critical infrastructure enhancement.

Research results, if successful, may help future cities in many ways. Next generation GPS and positioning may make it possible to locate E-911 callers inside high-rise buildings or underground spaces. Higher resolution and continuous remote sensing may help monitor sensitive areas, map tree species (e.g., ash) or poorly-insulated buildings and create high-fidelity maps for self-driving vehicles. Spatial databases may help cities identify under-served areas and geographic interdependence across infrastructures (e.g., water main above a train tunnel with a crucial optical fiber) to improve access and resilience. Spatial data science may identify infrastructure deprivation hotspots and their correlates (e.g., co-locations, tele-connections) to generate hypotheses for theory formation.

Research should go beyond technology to consider societal issues, since technological developments often pose dilemmas for society [96]. An understanding of these dilemmas may help guide an appropriate reaction to such changes. For example, increased use of surveillance cameras can increase a city's monitoring and security capabilities, but it also reduces individuals' privacy [97]. Such concerns need to be resolved with increased awareness and community engagement to improve the adaptability of technology within the community. Furthermore, there is a need to formulate thoughtful policies that align new technologies with societal needs.

Acknowledgment

This material is based upon work supported by the National Science Foundation under Grants No. 1541876, 1029711, IIS-1320580, 0940818 and IIS-1218168, the USDOD under Grants No. HM1582-08-1-0017 and HM0210-13-1-0005, ARPA-E under Grant No. DE-AR0000795, USDA under Grant No. 2017-51181-27222, NIH under Grant No. UL1 TR002494, KL2 TR002492 and TL1 TR002493 and the OVPR Infrastructure Investment Initiative and Minnesota Supercomputing Institute (MSI) at the University of Minnesota. We thank our NSF Smart and Connected Communities project parteners, namely, Hennepin County, and cities of Minneapolis, St. Paul and Tallahassee for sharing use-cases and datasets. We would like to thank Jamal Golmohammadi for helping with the figures and Kim Koffolt, Samantha Detor and the spatial computing research group for their helpful comments and refinement.

References

[1] American Psychological Association, "Toward an urban psychology: Research, action, and policy," *Washington, DC: Author*, 2005.

[2] T. Hartig, R. Mitchell, S. De Vries, and H. Frumkin, "Nature and health," *Annual review of public health*, vol. 35, pp. 207–228, 2014.

[3] A. Ramaswami, A. G. Russell, P. J. Culligan, K. R. Sharma, and E. Kumar, "Meta-principles for developing smart, sustainable, and healthy cities," *Science*, vol. 352, no. 6288, pp. 940–943, 2016.

[4] U. SDGs, "United nations sustainable development goals," 2015.

[5] "4th ieee international smart cities conference (isc2)," https://bit.ly/2vn20bl, 2018.

[6] B. Obama, "Presidential policy directive 21: Critical infrastructure security and resilience," *Washington, DC*, 2013.

[7] P. Tullis, "The world economy runs on gps. it needs a backup plan," 2018. [Online]. Available: https://bloom.bg/2mGg8IN

[8] J. A. Peterson, *The birth of city planning in the United States, 1840–1917*. JHU Press, 2003.

[9] M. Batty, K. W. Axhausen, F. Giannotti, A. Pozdnoukhov, A. Bazzani, M. Wachowicz, G. Ouzounis, and Y. Portugali, "Smart cities of the future," *The European Physical Journal Special Topics*, vol. 214, no. 1, pp. 481–518, 2012.

[10] M. Batty, *Big data and the city*. Alexandrine Press, 2016.

[11] N. Cressie, "Statistics for spatial data," *Terra Nova*, vol. 4, no. 5, pp. 613–617, 1992.

[12] S. Shekhar, S. K. Feiner, and W. G. Aref, "Spatial computing," *Communications of the ACM*, vol. 59, no. 1, pp. 72–81, 2015.

[13] C. Yin, Z. Xiong, H. Chen, J. Wang, D. Cooper, and B. David, "A literature survey on smart cities," *Science China Information Sciences*, vol. 58, no. 10, pp. 1–18, 2015.

[14] T. Shelton, M. Zook, and A. Wiig, "The actually existing smart city," *Cambridge Journal of Regions, Economy and Society*, vol. 8, no. 1, pp. 13–25, 2015.

[15] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything you wanted to know about smart cities: The internet of things is the backbone," *IEEE Consumer Electronics Magazine*, vol. 5, no. 3, pp. 60–70, 2016.

[16] M. Angelidou, "Smart city policies: A spatial approach," *Cities*, vol. 41, pp. S3–S11, 2014.

[17] Y. Zheng, L. Capra, O. Wolfson, and H. Yang, "Urban computing: concepts, methodologies, and applications," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 5, no. 3, p. 38, 2014.

[18] A. Gruen, "Smart cities: The need for spatial intelligence," *Geo-spatial Information Science*, vol. 16, no. 1, pp. 3–6, 2013.

[19] J. Grenslitt, "15th annual digital cities survey - 2015 results," 2015. [Online]. Available: https://bit.ly/1kpWDAO

[20] J. Grenslitt, "Digital cities survey 2016 winners announced," 2016. [Online]. Available: https://bit.ly/2elsSmy

[21] J. Grenslitt, "Digital cities survey 2017 winners announced," 2017. [Online]. Available: https://bit.ly/2mbZe7E

[22] W. Lechner and S. Baumann, "Global navigation satellite systems," *Computers and Electronics in Agriculture*, vol. 25, no. 1-2, pp. 67–85, 2000.

[23] Y. Masumoto, "Global positioning system," May 11 1993, uS Patent 5,210,540.

[24] R. T. Brunts, "Gps based time determining system and method," Mar. 3 1998, uS Patent 5,724,316.

[25] C. Caron, D. Chamberland-Tremblay, C. Lapierre, P. Hadaya, S. Roche, and M. Saada, "Indoor positioning," in *Encyclopedia of GIS*. Springer, 2008, pp. 553–559.

[26] D. Han, S. Jung, M. Lee, and G. Yoon, "Building a practical wi-fi-based indoor navigation system," *IEEE Pervasive Computing*, vol. 13, no. 2, pp. 72–79, 2014.

[27] L. Ran, S. Helal, and S. Moore, "Drishti: an integrated indoor/outdoor blind navigation system and service," in *Pervasive Computing and Communications, 2004. PerCom 2004. Proceedings of the Second IEEE Annual Conference on*. IEEE, 2004, pp. 23–30.

[28] R. L. Showen and J. W. Dunham, "Automatic real-time gunshot locator and display system," Oct. 26 1999, uS Patent 5,973,998.

[29] I. Schweizer, R. Bärtl, A. Schulz, F. Probst, and M. Mühläuser, "Noisemap-real-time participatory noise maps," in *Second International Workshop on Sensing Applications on Mobile Phones*. Citeseer, 2011, pp. 1–5.

[30] P. E. K. Fiedler and P. H. T. Zannin, "Evaluation of noise pollution in urban traffic hubsnoise maps and measurements," *Environmental Impact Assessment Review*, vol. 51, pp. 1–9, 2015.

[31] E. Eftelioglu, X. Tang, and S. Shekhar, "Avoidance region discovery: A summary of results," in *Proceedings of the 2018 SIAM International Conference on Data Mining*. SIAM, 2018, pp. 585–593.

[32] "National Agriculture Imagery Program," https://bit.ly/2kBQbKM, 2018.

[33] "Lidar elevation data for minnesota," http://www.mngeo.state.mn.us/chouse/elevation/lidar.html, 2018.

[34] D. Konstantinidis, T. Stathaki, V. Argyriou, and N. Grammalidis, "Building detection using enhanced hog–lbp features and region refinement processes," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 10, no. 3, pp. 888–905, 2017.

[35] N. Kussul, M. Lavreniuk, S. Skakun, and A. Shelestov, "Deep learning classification of land cover and crop types using remote sensing data," *IEEE Geoscience and Remote Sensing Letters*, vol. 14, no. 5, pp. 778–782, 2017.

[36] L. P. Rampi, J. F. Knight, and M. Bauer, "Minnesota land cover classification and impervious surface area by landsat and lidar: 2013 update," http://doi.org/10.13020/D6JP4S, 2016.

[37] M. L. Imhoff, P. Zhang, R. E. Wolfe, and L. Bounoua, "Remote sensing of the urban heat island effect across biomes in the continental usa," *Remote Sensing of Environment*, vol. 114, no. 3, pp. 504 – 513, 2010.

[38] M. K. Jat, P. Garg, and D. Khare, "Monitoring and modelling of urban sprawl using remote sensing and gis techniques," *International Journal of Applied Earth Observation and Geoinformation*, vol. 10, no. 1, pp. 26 – 43, 2008. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0303243407000335

[39] "Minnesota solar suitability analysis," http://solar.maps.umn.edu/, 2018.

[40] M. Rylatt, S. Gadsden, and K. Lomas, "Gis-based decision support for solar energy planning in urban environments," *Computers, Environment and Urban Systems*, vol. 25, no. 6, pp. 579–603, 2001.

[41] R. Compagnon, "Solar and daylight availability in the urban fabric," *Energy and buildings*, vol. 36, no. 4, pp. 321–328, 2004.

[42] Y. Xie, E. Eftelioglu, R. Y. Ali, X. Tang, Y. Li, R. Doshi, and S. Shekhar, "Transdisciplinary foundations of geospatial data science," *ISPRS International Journal of Geo-Information*, vol. 6, no. 12, p. 395, 2017.

[43] M. Kulldorff, "A spatial scan statistic," *Communications in Statistics-Theory and methods*, vol. 26, no. 6, pp. 1481–1496, 1997.

[44] D. B. Neill, A. W. Moore, M. Sabhnani, and K. Daniel, "Detection of emerging space-time clusters," in *Proceedings of the eleventh ACM SIGKDD international conference on Knowledge discovery in data mining*. ACM, 2005, pp. 218–227.

[45] E. Eftelioglu, S. Shekhar, D. Oliver, X. Zhou, M. R. Evans, Y. Xie, J. M. Kang, R. Laubscher, and C. Farah, "Ring-shaped hotspot detection: a summary of results," in *Data Mining (ICDM), 2014 IEEE International Conference on*. IEEE, 2014, pp. 815–820.

[46] X. Tang, E. Eftelioglu, D. Oliver, and S. Shekhar, "Significant linear hotspot discovery," *IEEE Transactions on Big Data*, vol. 3, no. 2, pp. 140–153, 2017.

[47] R. Y. Ali, V. M. Gunturi, A. J. Kotz, S. Shekhar, and W. F. Northrop, "Discovering non-compliant window co-occurrence patterns: A summary of results," in *International Symposium on Spatial and Temporal Databases*. Springer, 2015, pp. 391–410.

[48] J. M. Kang, S. Shekhar, C. Wennen, and P. Novak, "Discovering flow anomalies: A sweet approach," in *Data Mining, 2008. ICDM'08. Eighth IEEE International Conference on*. IEEE, 2008, pp. 851–856.

[49] S. Denyer, "Beijing bets on facial recognition in a big drive for total surveillance," https://wapo.st/2ABUaAB, 2018.

[50] C. A. Rahman, W. Badawy, and A. Radmanesh, "A real time vehicle's license plate recognition system," in *Advanced Video and Signal Based Surveillance, 2003. Proceedings. IEEE Conference on*. IEEE, 2003, pp. 163–166.

[51] A. Romero, C. Gatta, and G. Camps-Valls, "Unsupervised deep feature extraction for remote sensing image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 3, pp. 1349–1362, 2016.

[52] Y. Tong, Y. Chen, Z. Zhou, L. Chen, J. Wang, Q. Yang, J. Ye, and W. Lv, "The simpler the better: a unified approach to predicting original taxi demands based on large-scale online platforms," in *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 2017, pp. 1653–1662.

[53] "Earth on aws," https://aws.amazon.com/earth/, 2018.

[54] S. P. Department, "Online crime maps," 2018. [Online]. Available: https://www.seattle.gov/police/information-and-data/online-crime-maps

[55] C. of Chicago, "Crimes - map," 2018. [Online]. Available: https://data.cityofchicago.org/Public-Safety/Crimes-Map/dfnk-7re6/data

[56] CTA, "Transit trackers," 2018. [Online]. Available: https://www.transitchicago.com/tracker/

[57] W. Mobile, "Waze," 2018. [Online]. Available: https://www.waze.com/

[58] P. Safety and H. Security, "911 and e911 services," May 2018. [Online]. Available: https://www.fcc.gov/general/9-1-1-and-e9-1-1-services

[59] F. A. Administration, "No drone zone," Jul 2017. [Online]. Available: https://www.faa.gov/uas/where_to_fly/no_drone_zone/

[60] H. S. Puri, "How the smart cities project is transforming india's urban governance," Jul 2018. [Online]. Available: https://bit.ly/2MP4A0N

[61] A. Charles, "Case study japan: Gis-technologies in urban planning," Jun 2017. [Online]. Available: https://bit.ly/2swkbMH

[62] W. Shi, S. Shen, and Y. Liu, "Automatic generation of road network map from massive gps, vehicle trajectories," in *Intelligent Transportation Systems, 2009. ITSC'09. 12th International IEEE Conference on*. IEEE, 2009, pp. 1–6.

[63] J. Chen and M. Bierlaire, "Probabilistic multimodal map matching with rich smartphone data," *Journal of Intelligent Transportation Systems*, vol. 19, no. 2, pp. 134–148, 2015.

[64] Q. Lu, B. George, and S. Shekhar, "Capacity constrained routing algorithms for evacuation planning: A summary of results," in *International symposium on spatial and temporal databases*. Springer, 2005, pp. 291–307.

[65] D. LaST, "Gnss: The present imperfect," *Inside GNSS*, vol. 5, no. 3, pp. 60–64, 2010.

[66] G. Fisher and J. Kunches, "Building resilience of the global positioning system to space weather," *Space Weather*, vol. 9, no. 12, 2011.

[67] K. Nogueira, O. A. Penatti, and J. A. dos Santos, "Towards better exploiting convolutional neural networks for remote sensing scene classification," *Pattern Recognition*, vol. 61, pp. 539–556, 2017.

[68] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, *Deep learning*. MIT press Cambridge, 2016, vol. 1.

[69] K. Nogueira, O. A. Penatti, and J. A. dos Santos, "Towards better exploiting convolutional neural networks for remote sensing scene classification," *Pattern Recognition*, vol. 61, pp. 539–556, 2017.

[70] "Emerald ash borer," https://bit.ly/2Mf4sYP, 2018.

[71] BBC News, "Ash tree set for extinction in europe," http://www.bbc.com/news/science-environment-35876621, 2016.

[72] S. H. Lee, C. S. Chan, P. Wilkin, and P. Remagnino, "Deep-plant: Plant identification with convolutional neural networks," in *Image Processing (ICIP), 2015 IEEE International Conference on*. IEEE, 2015, pp. 452–456.

[73] M. Dalponte, L. Bruzzone, and D. Gianelle, "Tree species classification in the southern alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and lidar data," *Remote sensing of environment*, vol. 123, pp. 258–270, 2012.

[74] "Transdisciplinary research in principles of data science (tripods)," https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=505347, 2018.

[75] Z. Jiang, S. Shekhar, X. Zhou, J. Knight, and J. Corcoran, "Focal-test-based spatial decision tree learning: A summary of results," in *Data Mining (ICDM), 2013 IEEE 13th International Conference on*. IEEE, 2013, pp. 320–329.

[76] Y. Xie and S. Shekhar, "Ff-sa: Fragmentation-free spatial allocation," in *International Symposium on Spatial and Temporal Databases*. Springer, 2017, pp. 319–338.

[77] Y. Huang, S. Shekhar, and H. Xiong, "Discovering colocation patterns from spatial data sets: a general approach," *IEEE Transactions on Knowledge and Data Engineering*, vol. 16, no. 12, pp. 1472–1485, 2004.

[78] S. Openshaw, "The modifiable areal unit problem," *Concepts and techniques in modern geography*, 1984.

[79] D. Wong, "The modifiable areal unit problem (maup)," *The SAGE handbook of spatial analysis*, pp. 105–123, 2009.

[80] N. Pokhriyal and D. C. Jacques, "Combining disparate data sources for improved poverty prediction and mapping," *Proceedings of the National Academy of Sciences*, vol. 114, no. 46, pp. E9783–E9792, 2017.

[81] R. F. Austin, D. P. DiSera, and T. J. Brooks, *GIS for Critical Infrastructure Protection*. CRC Press, 2015.

[82] D. B. Neill, A. W. Moore, M. Sabhnani, and K. Daniel, "Detection of emerging space-time clusters," in *Proceedings of the eleventh ACM SIGKDD international conference on Knowledge discovery in data mining*. ACM, 2005, pp. 218–227.

[83] S. K. Prasad, D. Aghajarian, M. McDermott, D. Shah, M. Mokbel, S. Puri, S. J. Rey, S. Shekhar, Y. Xe, R. R. Vatsavai *et al.*, "Parallel processing over spatial-temporal datasets from geo, bio, climate and social science communities: A research roadmap," in *Big Data (BigData Congress), 2017 IEEE International Congress on*. IEEE, 2017, pp. 232–250.

[84] "Facial recognition is accurate, if you're a white guy," https://nyti.ms/2H3QeaT, 2018.

[85] O. Wolfson and J. Lin, "Fairness versus optimality in ridesharing," in *Mobile Data Management (MDM), 2017 18th IEEE International Conference on*. IEEE, 2017, pp. 118–123.

[86] R. Y. Ali, E. Eftelioglu, S. Shekhar, S. Athavale, and E. Marsman, "Supply-demand ratio and on-demand spatial service brokers: a summary of results," in *Proceedings of the 9th ACM SIGSPATIAL International Workshop on Computational Transportation Science*. ACM, 2016, pp. 7–12.

[87] P. Voigt and A. Von dem Bussche, *The EU General Data Protection Regulation (GDPR)*. Springer, 2017, vol. 18.

[88] Y. Li, K. Fu, Z. Wang, C. Shahabi, J. Ye, and Y. Liu, "Multi-task representation learning for travel time estimation," in *International Conference on Knowledge Discovery and Data Mining,(KDD)*, 2018.

[89] D. Wang, J. Zhang, W. Cao, J. Li, and Y. Zheng, "When will you arrive? estimating travel time based on deep neural networks." AAAI, 2018.

[90] R. Y. Ali, Y. Li, S. Shekhar, S. Athavale, and E. Marsman, "Supply and demand aware synthetic data generation for on-demand traffic with real-world characteristics," in *Proceedings of the 10th ACM SIGSPATIAL Workshop on Computational Transportation Science*. ACM, 2017, pp. 36–41.

[91] "CityGML," https://www.citygml.org/, 2018.

[92] H.-K. Kang and K.-J. Li, "A standard indoor spatial data modelogc indoorgml and implementation approaches," *ISPRS International Journal of Geo-Information*, vol. 6, no. 4, p. 116, 2017.

[93] C. Eastman, P. Teicholz, R. Sacks, and K. Liston, *BIM handbook: A guide to building information modeling for owners, managers, designers, engineers and contractors*. John Wiley & Sons, 2011.

[94] "BIM and sensor data," https://bit.ly/2Mf8sbJ, 2018.

[95] K. Yang and S. Shekhar, "Capacity constrained network voronoi diagrams," in *Spatial Network Big Databases*. Springer, 2017, pp. 27–45.

[96] U. Dolata, "Technological innovations and sectoral change: Transformative capacity, adaptability, patterns of change: An analytical framework," *Research policy*, vol. 38, no. 6, pp. 1066–1076, 2009.

[97] A. Cavallaro, "Privacy in video surveillance [in the spotlight]," *IEEE Signal Processing Magazine*, vol. 2, no. 24, pp. 168–166, 2007.