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Today, vast volumes of highly diverse sensor data are generated, and this amount is growing exponentially. As highlighted in several chapters of this book, high-AQ1 resolution remotely sensed data serve day-to-day applications. Virtual Globes such as Google Earth have brought such images to everybody's fingertips. Lesser known to the wider public are two other fields of data generation: real-time in situ sensing of environmental parameters and sensing of human behavior in space and time. Environmental data are mainly sensor-generated. Examples include weather stations or intelligent mobile sensor pods. We call these "machine-generated" data. On the contrary, direct measurements of humans in space and time are predominantly restricted for privacy reasons. Information about persons or groups and their behavior in space and time is either derived from so-called volunteered geographic information (VGI) or it may be derived from proxy data, for example, from mobile communication networks or social media. In this chapter, we argue that multiple coordinated views of spatiotemporal data provide unprecedented opportunities for geographic analysis in times of "big data." Together, these different types of data generation enable an integrated sensing. We focus on urban areas where the density

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of relevant information is already high. We claim that integrated urban sensing opens new vistas to physical and social dynamics at the environment-human interface. We analyze the intersection of machine-generated (satellite imagery, weather stations) and user-generated (social media, mobile phone data) data and we contend that geographic information systems (GIS) as a tool and geographic information science (GIScience) principles are together the lynchpin of integrated urban sensing. In particular, GIS plays a major role in urban monitoring studies. We demonstrate that GIS-based integrated urban sensing enables analyses, forecasts, and visualizations of a variety of spatial components of socioeconomic phenomena. This includes people, urban commodities, and their respective changes, but also information flows and human interaction with urban commodities as well as the relationships among networks of human interaction and natural environments.

14.1 INTRODUCTION

At the beginning of the twenty-first century, a wide range of technologies are able to sense, directly or indirectly, a variety of environmental, human, and social phenomena—thereby facilitating the "Digital Earth" concept introduced by Gore (1998). Such sensing technologies generate vast and rapidly increasing volumes of digital sensor data. It is claimed that these data may at least partially reflect the dynamics of both environmental and social phenomena in remarkable spatial and temporal detail, and thus open novel research opportunities for the GIScience domain as well (cf. Annoni et al., 2011, Goodchild et al., 2012, Hey et al., 2009).

The focus of this chapter is on urban areas. Conceptually, the methods described would work everywhere the information content is dense enough. We avoid a discussion on what "dense enough" means when targeting cities. The term "city" comprises not only a geographical area characterized by a dense accumulation of people or buildings, but implicitly includes a multilayered construct containing multiple dimensions of social, technological, and physical interconnections and services (Blaschke et al., 2011).

In this chapter, we will discuss concepts which in synopsis may support our vision of integrated urban sensing. In the empirical part, we will concentrate on the research question of how the spatial and temporal nature of the acquired data might be characterized. The hypothesis is that rather than utilizing relatively small samples of individuals, as social sciences may have to, we can gain insights into a "collective behavior" which may characterize some aspects of urban life. The aim is to abstract beyond individual characteristics of probes—moving objects in general including humans and commodities. We will demonstrate methods to analyze, visualize, and explain some of the patterns we identified. The results are not immediately scalable to larger studies but we could prove the appropriateness of the methods in several earlier studies (Sagl et al., 2011, 2012a–c). Indubitably, we build on the ideas of Resch and coworkers (Resch et al., 2011, 2012a,b).

Resch et al. (2012b) even suggest a concept of a "live city," in which the city is regarded as an actuated near real-time control system creating a feedback loop between the citizens, environmental monitoring systems, the city management, and ubiquitous information services, thereby facilitating the "smart city" concept.

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In this chapter, we will utilize the clarification of the term "live"—as opposed to common understanding of "near real time"—of Resch et al. (2012b) but we will stay at the analytical level. The aim is to report on the methods of integrated urban sensing, and we will leave out a discussion of a "Live City." Such a discussion would need to comprehensively cover privacy and legislative issues. Nevertheless, a visionary outlook can be provided. On purpose, such an outlook is limited to the analytical capabilities and excludes anticipated societal developments. Some analytical capabilities will be demonstrated and it will be briefly discussed as to whether this potential may lead to new vistas of space-time analysis.

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Within the context of "Live City" and "Smart City," the need of an advanced understanding of environmental and social dynamics such as the weather or human behavior is obvious. This also refers to the broad spectrum of sustainable resource management and its various application domains such as electricity, heat, water, transportation, and urban planning as well as safety, security, health care, etc. The cross-integration of multiscale ubiquitous sensor data into spatial, temporal, and spatiotemporal analysis can potentially enhance our understanding of resources' demand and, thus, their efficient allocation (cf. Hancke et al., 2013). Hence, integrated urban sensing enables a more holistic view on urban phenomena and processes, thereby facilitating the concepts of live and smart cities. In fact, integrated urban sensing might be a promising way for quantifying urban performance with respect to both the physical as well as the social and human capital (Ho Van et al., 2009).

The research in the context of integrated urban sensing is diverse. An increasing amount of scholars aim to explore the possibilities of statistical methods of analysis that are better suited for the peculiarities of space-time data. GIS methods are at the core of such options. GIS-based spatial analysis techniques can help unlock and visualize the substantial spatial and temporal components of the geographic phenomena of interest. In addition to the scientific value of such techniques, GIS enables researchers to generate sophisticated visualizations and computer animations that are useful for education. Ultimately, such visualizations serve to convey the results of research on urban systems to a wider public (Blaschke et al., 2012).

In this chapter, we address the need for multiscale integrated sensing for crossscale integrated monitoring of urban spaces. We do so by linking together three dimensions involved in sensing: machine- or user-generated data, the underlying geographic phenomena, and the type of sensing (Figure 14.1). "Scale" herein refers to both temporal and spatial scales and can be seen as the overarching meta-dimension in the context of sensing, analyzing, and monitoring geographic phenomena. We rely on the concepts of GIScience (Goodchild, 2010) but we do not discuss the role of GIScience as such. There is a significant body of literature about what exactly makes spatial special (e.g., Goodchild, 1991) and we refer to Blaschke and Strobl (2010), who orchestrate various trends and developments in this field under 10 themes.

Specifically, we focus on environmental data, human data including their mobility, and social data. In the following sections, we present several case studies of how "sensors" and "sensor networks" in combination with GIScience concepts can be employed to investigate spatial and temporal characteristics of physical and social phenomena across multiple spatial and temporal scales.

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FIGURE 14.1 Dimensions involved in sensing.

14.2 TRIPLE D: DIMENSIONS, DOMAINS, AND DATA OF INTEGRATED URBAN SENSING

In this section, we illustrate and interlink dimensions, domains, and data in the context of integrated urban sensing (Figure 14.2). For instance, social sensor data (representing some social phenomena) are predominately user-generated and sensed in situ while environmental sensor data (representing some physical phenomena) are typically machine-generated (view 2 and 3); there are hardly any sensor data that



FIGURE 14.2 Blocks of sensor data assigned to the dimensions of sensing: (a) in 3D and (b) from a top/front/side perspective.

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are sensed remotely and generated by users (view 1). Although such links between AQ2 sensor data and dimensions of sensing might be obvious, they

Some examples of data types corresponding to Figure 14.2 are as follows:

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- 1. VGI and mobile network traffic
- 2. VGI in the context of environmental status updates
- 3. Satellite imagery
- 4. Measurements from sensors and sensor networks

5. Human settlements extracted from satellite imagery

6. Counter data at entrances and exits of shopping malls, public transport, etc.

14.2.1 CHARACTERIZING DOMAINS OF URBAN SENSING

Sensors and sensor networks generate digital representations of the Earth's surface, or measure the healthiness of vegetation, or the pressure of a snow pack which could potentially destroy a rooftop. Most prominent examples of sensors are weather stations. They measure air temperature, rain fall, solar radiation, particulate matter, etc. They are therefore multisensor stations. Likewise, satellites carry multiple sensors which measure reflectance values of atmospheric parameters such as ozone. However, many sensors, as well as the generation of sensor data, can be characterized in a binary manner (Table 14.1). For instance, air temperature is typically measured periodically and on purpose using a single sensor calibrated in situ that generates accurate measurements. On the other hand, the user-generated traffic in mobile phone networks is managed by the network's backend in order to enable mobile people to communicate wirelessly almost everywhere at any time. As a byproduct, the log files from such a backend can reflect the human behavior patterns of millions of mobile users in remarkable spatial and temporal detail. Therefore, the mobile network, which is not intended for sensing, can, however, be used indirectly as a large-scale sensor for human behavior.

TABLE 14.1 Binary Characterization of Sensor Devices and Sensor Data: Some Examples

In situ	Remote			
Single sensor	Multiple sensor			
Terrestrial	Aquatic			
Machine-generated	User-generated			
Singularly	Periodical			
Direct	Indirect			
On purpose	Not intent for sensing			
Demanded	By-product			
Voluntarily provided	Involuntarily provided			

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	Availability	Accessibility	Resolution	Integratability	"Degree of Efficiency"	Cost/Benefit Ratio	Privacy Concerns
Stand-alone sensors							
Geo-sensor networks							
Space-based sensors							(1)
Mobile networks					(2)	(3)	(4)
Crowd sourcing and VGI							
People as sensors		(5)					

FIGURE 14.3 Examples of urban sensing techniques and weighting of other characteristics regarding sensor data (light gray = low/bad, gray = moderate/medium, dark gray = high/good); (1) specifically high-resolution imagery; (2) well-established infrastructure; (3) requires no additional investment; (4) depending on the aggregation level; (5) if available, then accessible.

- AQ4 In Figure 14.3, we make an attempt to contrast the following additional characteristics of urban sensing techniques by using three levels: low/bad, moderate/medium, and high/good.
 - Availability refers to existence and quantity of sensor data.
 - Accessibility depends on availability and refers to the easiness of data access.
 - *Resolution* refers to the spatial, temporal, as well as thematic (i.e., qualitative) granularity.
 - *Integratability* refers to the easiness of including sensor data in analysis workflows.
 - *Degree of efficiency* is the ratio between information achieved and technical complexity.
 - *Cost/benefit ratio* shows the data's added value considering the monetary investment.
 - Privacy concerns refer to the impingement upon individual or collective privacy rights.

In addition to machine-generated sensor data, the data generated and shared via the Internet voluntarily by individuals (summarized by the term VGI; Goodchild, 2007) and the data generated but shared involuntarily by users of digital systems (e.g., using a mobile phone within a mobile network and thereby generating network traffic) represent an increasingly large and broad sample of the society's behavior (cf. Shoval, 2007).

Different sensors and sensing technologies generate sensor data that represent a geographic phenomenon of interest at different spatial and temporal granularity: remotely sensed data typically have a lower spatial and a lower temporal resolution than in situ sensed data but comprise wider coverage. On the other hand, the granularity of VGI or data from social media is even far from being constant, as is their spatial accuracy, their semantics, and many other data quality parameters.

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However, the volume and sample size of data are exploding (Hey et al., 2009), not least due to the use of "thick" mobile devices such as smart phones, which are typically constantly connected to the Internet, social media, and other services of the Web 2.0.

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Therefore, we will distinguish two major groups of data. Environmental data are mainly generated by "real" sensors, for instance, weather stations or intelligent mobile sensor pods. We call these "machine-generated" data. On the contrary, direct measurements of humans in space and time are predominantly restricted for privacy reasons. Information about persons or groups and their behavior in space and time is derived either from VGI or from proxy data. Proxy data can stem from, for instance, mobile communication networks or social media. For simplicity, we call this second group "user-generated" data (refer to Figure 14.3).

14.2.2 WHY ARE REMOTE SENSING DATA LEFT OUT HERE?

Although remote sensing is at the core of this book, we will refrain from covering remote sensing concepts herein. Rather, we will focus on other aspects of "Earth observation." First, all the other 17 chapters in this book describe in detail remote sensing platforms and sensors, methods of data acquisition and analysis, and interpretation. Second, remotely sensed data are often seen as the process of generating thematic interpretations from digital signals that model parts of the Earth's surface. Following this definition, we would use the results as thematic layers in integrated sensing applications as categorical data, usually from interval to nominal levels of measurement. Third, Blaschke et al. (2011) have already focused on the integration of remote sensing and other forms of sensing for urban applications. Unclassified image data may be more "objective" and have a greater range of measurement but many applications require classified thematic interpretations. This way, we hope to be able to contribute to more holistic and integrative urban observation systems.

In particular, we postulate non–remote sensing data to be crucially important for the following functions:

- 1. Characterizing urban ecosystems, built environment, air quality, and carbon emission
- 2. Developing indicators of population density, environmental quality, and quality of life
- 3. Characterizing patterns of human, environmental, and infectious diseases

These points reflect goals of the Group of Earth Observation (GEO) task SB-04-C1— Global Urban Observation and Information, for which this book is planned to be a major contribution. We strongly believe that remote sensing data are undoubtedly at the core of these tasks but non–remote sensing (in situ, social network, etc.) data are indispensible, too, and we therefore concentrate on the latter. For example, remote sensing data together with climatological station data are the starting point for modeling urban climate, microclimatological parameters, and phenomena like urban heat islands. Nevertheless, in order to better understand the impacts of global climate

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change on urban areas, validations are needed and the "people's view" needs to be incorporated—which is a ground view. We postulate that in most cases up to date, people-centered information on the status and development of urban environments and personal spaces will be needed. They may not only be used to fill gaps in global urban observations but they will in the future be indispensible when characterizing urban ecosystems, population density in built-up environment, air quality, environmental quality, and carbon emission.

For the sake of completeness, it must be stated that remote sensing also delivers data that are used as proxies for environmental parameters without classification. Well-known examples include the Normalized Differenced Vegetation Index (NDVI), the Leaf Area Index (LAI), and land surface temperature (LST), which can be used directly in integrated urban sensing and analysis.

We conclude that remote sensing is a mature technology, particularly for largerscale observations, that has been significantly utilized in a world increasingly employing geospatial data. However, fine-grained urban remote sensing data are—aside from numerous case studies—hardly available across large areas. In the remainder of this chapter, we will therefore focus on additional and emerging sensing methods that are supposedly less familiar to the audience of this book.

14.2.3 Environmental Sensing: "Machine-Generated" Data

Environmental sensing, environmental analysis, and environmental monitoring are all well-established fields. The fields may overlap, the terms may be used ambiguously by different communities and their methodologies, and paradigms may undergo changes. They are, nevertheless, not new and do not need to be discussed in detail herein.

What is relatively new is the IT framework-typically referred to as the Sensor Web (cf. Delin and Jackson, 2001, Resch, 2012, Zyl et al., 2009)-which enables complex combinations of sensing methods and arrangements of different sensing devices to assess a variety of environmental phenomena. Furthermore, information had to often be constructed out of data only retrospectively, that is, the data acquisition was totally decoupled from the data analysis. Sagl et al. (2012d) describe an exercise where mobile radioactive radiation sensor measurements were spatially interpolated in near real time for supporting rescue forces in time-critical decision making. Although not a typical urban sensing scenario, this can convincingly illustrate the advantage of creating timely information: in a classic workflow, experts would have gathered radiation information in the field and would have created maps containing isolines of certain radiation concentrations afterward. Such a classic mapping exercise could take hours, which could be critical in this example. Sagl et al. (2012d) could show that near-real time and fully automated analysis workflows based on standardized services speed up this process significantly while hiding the heterogeneity of underlying sensors and sensor networks. Purposely, we refer to the term "near real time" as it does not impose rigid deadlines but suggests the dynamic adaptation of a time period according to different usage contexts (Resch, 2012). The terms "live" and "near real time" are seemingly appropriate and used synonymously herein.

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14.2.4 HUMAN SENSING: "USER-GENERATED" DATA

The digital traces that people continuously leave behind—voluntarily or not—while using communication devices such as mobile phones or interacting with social media platforms reflect their behavior in great detail. These traces can be seen as social sensor data (Sagl et al., 2012c) and can serve as proxy for human activity and mobility. A spatial and temporal analysis of such proxy data can thus provide insights into the social dimension and, moreover, the functional configuration of complex urban systems.

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Herein we focus on the potential of user-generated data from mobile networks and social media. For instance, Sagl et al. (2012b) show that both characteristic and exceptional urban mobility patterns can be derived from handovers (i.e., movements between pairs of radio cells) within a mobile network. Such insights can help to better understand the daily "pulse" of urban movements in the city (Sevtsuk and Ratti, 2010), thereby providing additional information for, for example, public transportation management strategies. In the context of urban mobility, online social networks such as Foursquare can also be used to examine differences and similarities, and derive even universal laws, in human movements across several metropolitan areas around the globe (Noulas et al., 2012). In summary, such studies clearly demonstrate the significance of different user-generated "sensor" data for multiscale integrated urban analysis.

However, the different nature of user-generated data samples results in differences in terms of representativeness and semantic expressiveness: from a user's perspective, "involuntarily" provided mobile network traffic naturally represents a relatively large proportion of the population across social classes; however, it is typically lacking in content. For instance, the number of text messages sent/received is known but not the text itself, or the number and duration of calls is known but not the topic of the talk itself. This is in contrast to social media data, which, first, typically represent a rather specific subgroup of the population, and, second, contain content of some semantic value (e.g., the number and the text of Twitter messages, so-called tweets, are known). In addition, "when data collection is situated 'outside' the thing being studied, observation remains arguably neutral. But when data collection is embedded among the actors within a setting, as in participant observation, a cycle of interactivity is launched in which observation changes behavior that changes observation and so on" (Cuff et al., 2008, p. 28). These aspects shall be taken into account when analyzing user-generated data—or social sensor data in the context of integrated urban sensing.

14.2.5 COMBINING ENVIRONMENTAL WITH SOCIAL SENSING

Several approaches exist that aim to combine environmental (or physical) sensing with social sensing. Typically, such approaches are driven by different contexts. For instance, take the concept of "people as sensors": individual and context-dependent information directly complement sensor measurements of physical phenomena from well-calibrated hardware (Resch, 2013). Following this concept of complementing "real" sensor measurements, Hayes and Stephenson (2011)

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describe "online sensing" and use blogs, wikis, Twitter, Forums, etc., instead of "people as sensors" directly (although one may say that people are acting as sensors and putting data on these social media sources). In fact, they show how online sensors such as geo-coded images on Flickr or tags from Twitter messages can complement the temporal and spatial coverage of physical sensor measurements, even for cross-correlation. Kamel Boulos et al. (2011) provide a comprehensive review on overlapping domains of sensing including the Sensor Web and citizen sensing in the broad context of environmental and public health surveillance and crisis/disaster management. They argue that crowd sourcing allows for both horizontal and vertical sharing of environmental and social-related information, that is, between and among people using, for example, Twitter, Facebook, etc. (horizontally) or between people and other "machines" (vertically), such as comparing in-house prices with Amazon prices. They claim that "crowd reaching," which is supposed to be the counterpart of crowd sourcing, should be more established to reach the masses with useful and individualized information such as health tips. However, a clear distinction between crowd reaching and locationbased services (LBS) remains.

Rather than supporting or complementing data and information from and among different sources, Blaschke et al. (2011) argue for the integration of several geospatial technologies-including remote sensing-in order to gain a more holistic view on urban systems on different spatial and temporal scales. On a rather local or regional scale, Sagl et al. (2011) introduced an approach to bridge the gap between large-scale social sensing and environmental monitoring in order to potentially disclose insights into some instantaneous interactions between people and their environmental context factors. First, they derived basic weather conditions such as "normal" or "adverse" from time series of several meteorological variables (air temperature, rainfall, solar radiation, etc.). Second, these conditions were then linked to aggregated mobile phone usage, which served as a proxy for the collective human behavior, using frequency domain analysis methods. In order to take into account the spatial and temporal domain, this approach was developed further and resulted in the "context-aware analysis approach," which allows for investigating one geographic phenomenon in the context of another; moreover, it allows for quantifying environment-human relationship aspects (Sagl et al., 2012a).

Thus, in the context of integrated urban sensing, diverse technologies can be seen as sensors or sensor networks that are able to generate sensor data reflecting the underlying geographic phenomenon in great detail, thereby contributing to a more holistic understanding of urban phenomena.

14.3 CASE STUDIES

We present three case studies which demonstrate how sensor data from different sensing technologies are combined. Additionally, we present a conceptual framework for fully integrating both environmental and social dynamics. GIScience concepts are implicitly or explicitly used to investigate physical and social phenomena in both time and space.

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14.3.1 COLLECTIVE URBAN DYNAMICS

The first example is adopted from Sagl et al. (2012c) for this book chapter. It demonstrates user-generated mobile network traffic and geo-tagged photos from Flickr (a social media platform) can be used to provide additional insights into how collective social activity shapes urban systems. We used different geo-visualization techniques to effectively communicate such insights.

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Figure 14.4 shows the overall activity in a mobile network within the course of a typical working day in the city of Udine, northern Italy. While the city center



FIGURE 14.4 (See color insert.) Collective human activity in the city (Udine, northern Italy)—spatiotemporal mobile communication activity on a typical working day as seen from a mobile network operator's perspective. (From Sagl, G. et al., From social sensor data to collective human behaviour patterns: Analysing and visualising spatio-temporal dynamics in urban environments, in Jekel, T., Car, A., Strobl, J., and Griesebner, G., eds., *GI-Forum 2012: Geovisualization, Society and Learning*, Wichmann Verlag, Berlin, Germany, 2012c.)

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is clearly identifiable, the urban periphery behaves differently in the morning as compared to the evening. The actual Google Earth application behind these screenshots enables an advanced understanding of where and when people actively use the mobile network.

The second example is adopted from Sagl et al. (2012b). It shows that a purely visual analytics approach can be used to extract characteristic and exceptional urban mobility information from mobile network traffic, more specifically from the number of handovers (i.e., the number of movements between pairs of antennas). We show, among other things, the symmetry and similarity of the normalized mobility among four urban environments for each day of the week. On the scale of the main administrative urban unit, the overall urban mobility patterns show a surprisingly high degree of similarity and symmetry. All patterns show that the maximal total mobility is reached on Tuesday, closely followed by Wednesday; the minimal total mobility is clearly on Sunday. However, the absolute net migration flows start to diverge on Wednesday and converge again on Sunday. Gorizia, the smallest of the four cities, shows the comparably highest mobility activity on Friday and Saturday, which is confirmed as an asymmetric mobility behavior. In addition, we identified several exceptional patterns in the data and associated them to real-world events such as soccer matches or concerts. This enables an automated identification and classification of exceptional urban mobility behavior and thus potentially facilitates incident management.

14.3.2 CONTEXT-AWARE URBAN SPACES

The consolidation of environmental and social sensor data on a common spacetime basis enables a context-aware analysis, that is, the analysis of one geographic phenomenon in the context of another (e.g., human mobility in the context of the weather), thereby facilitating the identification and characterization of relationships, correlations, and possibly even causalities. In a first step, we focused on the evaluation of potential relations between phenomena of interest (e.g., between specific or even extreme weather conditions and the collective human mobility). This includes the use of established as well as the development of novel analysis methods and the evaluation of both. As described in detail in Sagl et al. (2012a), analysis methods from the time, space, and frequency domains have been applied in order to reveal relationships between weather and telecom data. In fact, using AO7 the maximal information coefficient (MIC) (Reshef et al., 2011), which is a novel statistic to measure the dependence for two-variable associations, we mapped the strength of that relationship back to the geographic space (Figure 14.5). The locations marked in white (Figure 14.5, L1 to L4) indicate that the strength of the relationship between adverse weather conditions and unusual human behavior correlates with the functional configuration of the city—in this case, locations with an obviously high degree of human dynamics: L1 covers a bus hub with a large parking lot; L2 covers the "Centro Studi Volta," a school for multidisciplinary activities; L3 is within a main residential area; and L4 is an official living place for nomadic people and gypsies.

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FIGURE 14.5 (See color insert.) Measuring the strength of the relationship between adverse weather conditions and unusual human activity using the MIC. 0, no relationship; 1, functional relationship. (Modified from Sagl, G. et al., *Sensors*, 12, 9835, 2012a.)

14.3.3 INTEGRATED SENSING FOR A MORE HOLISTIC GEO-PROCESS UNDERSTANDING

A variety of "sensors" and "sensor networks" can be used to systematically assess and monitor dynamic geographic phenomena at different spatial and temporal scales. However, the monitoring is typically done for each phenomenon individually (e.g., for air temperature or mobility). In order to enhance—or at least verify—our understanding of both environmental and social processes for multidisciplinary studies, a more holistic monitoring framework is needed. One way to fully integrate the spatiotemporal dynamics of both environmental and social phenomena is the "adaptive geo-monitoring framework" (Figure 14.6). It extends the "adaptive monitoring approach" (Lindenmayer and Likens, 2009) by adding the spatial dimension and the mutual context-awareness of dynamic geographic phenomena.

As described in more detail in Sagl (2012), the adaptive geo-monitoring framework enables further context-aware analysis approaches considering integrated (statistical) analysis methods from the space, time, and frequency domains. Sagl (2012) has demonstrated this concept for a small subset of potential applications. He explored spatial, temporal, and periodic relationships between basic weather conditions and some collective human behavior aspects.

The framework is designed to enable a more holistic process understanding of environmental and social phenomena across spatial and temporal scales. The term "adaptive" refers to, for instance, two or three spatial dimensions, zero or one temporal dimension, and *n* attribute dimensions; near-real time or "live" as well as postprocessing workflows; aggregation and decomposition of sensor data depending on the thematic focus (e.g., air quality as a composition of particulate matter, CO₂, NO_x, etc.); interpolation and extrapolation of the phenomenon of interest respecting

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FIGURE 14.6 Adaptive geo-monitoring, a conceptual framework for fully integrating environmental and social dynamics for enabling a more holistic process understanding.

different operational scales (e.g., diurnal and local versus seasonal and regional variability of air temperature); and hybrid reasoning methods by iteratively applying the inductive and deductive research approach.

Hence, the adaptive geo-monitoring approach potentially provides novel capabilities for examining the spatiotemporal behavior of physical and social phenomena through ubiquitous sensing and context-aware analysis.

14.4 DISCUSSION AND CONCLUSION

Within the overall realm of Global Urban Monitoring and Assessment—which is part of the title of this book—this chapter focused on integrated urban sensing. In contrast to the majority of chapters, remote sensing issues were widely excluded here although remote sensing plays a pivotal role for integrated sensing strategies of

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almost all kinds of information on the Earth's surface. The reason is that Blaschke et al. (2011) explicitly focused on the integration of remote sensing and other forms of sensing for urban applications and we aimed not to repeat ourselves.

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In a recent editorial, Tsou and Leitner (2013) postulated an emerging paradigm which aims at mapping cyberspace and social media. A special issue of the journal *Cartography and Geographic Information Science* provides discussions of social theories, innovative mapping methods, sentiment analysis, spatial modeling and statistics, space-time analysis, and geo-visualization examples within this field. We want to particularly highlight the contribution of Li et al. (2013) in this special issue: these authors provide an excellent overview of the big data study in social media by analyzing the spatial pattern of some 20 million Twitter messages and 4.2 million pictures from Flickr. These spatial patterns of big data prove a strong linkage between the uneven distribution of social media messages and the characteristics of local residents (messengers) cross-referenced from census data. Again, we may only be at a starting point of such developments—while remote sensing is believed to be a relatively mature field.

Our chapter highlighted only very few and limited examples within the realm of such trends, or even a paradigm shift as claimed by Tsou and Leitner. The urban social dynamics derived from user-generated sensor data demonstrate that "social sensor networks," specifically mobile networks and social media, significantly support our view on dynamic urban systems. From the novel context-aware analysis approach, we conclude that it is a promising way to provide insights into environment–human interface aspects, thereby potentially enabling a holistic process understanding of environmental and social dynamics in urban spaces.

However, we want to stress that we are aware that we had only explored isolated aspects of human-environment interaction. Such an analysis alone would be too reductionistic. Without venturing into a debate of environmental determinism, it is stated that many factors influence the collective human behavior. In this respect, weather is certainly only one factor that can influence human behavior. The respective case study in Section 14.3 therefore demonstrated mainly that correlations can be investigated-in principle. To what degree the results explain causalities will depend on the application. In fact, we need to be careful since many of the data sources and methods described in this chapter are used as proxies for processes that are much more complex. Such processes can only partially be explained by the datasets and methods used. For social behavior, one needs to critically examine the extent to which mobile phone data and particularly social media data may help us to better understand social communication behavior. Communication is not bound to mobile phone calls and texts. We cannot use these alone to learn about social communication although an increasing number of people use electronic means to communicate. Nevertheless, we strongly believe that our research outcomes can be the basis for further research on environment-human interface aspects and may stimulate interdisciplinary research activities toward the development of an adaptive framework for real-time monitoring and modeling of environment-human feedback loops.

After all these new technological opportunity potentials, the reader finally needs to be reminded of the limitations of all technology: any technology is at its best

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as good as a wise user has planned for it to be. We have stressed the increasing ability to add location to almost all existing information. Pathetically, we may claim that this will unlock the wealth of existing knowledge about social, economic, and environmental matters. Furthermore, it could play a vital role in understanding and addressing many of the challenges we face in an increasingly complex and interconnected world. Nevertheless, we are still at the beginning of an era of data affluence in mankind and we will have to guide day-to-day users in this field. There are many remaining and even some new issues of data privacy and new educational duties. In this respect, we do not believe that some space-time behavior analysis methods are now sold as new approaches to old problems only (Timmermans et al., 2002). Rather, new problems and new research questions arise.

Integrated urban sensing is a novel attempt to identify another dimension of cities as a "living space." The approach is clearly in its infancy, but we believe that we will soon see applications where decisions makers will use such information. Maybe a major in the future will better know where her or his people are at what time of the day. While integrated urban sensing will help us understand the spatiotemporal pattern of humans and of groups—even with anonymous and aggregated data—it will not tell us "why". In the times of "big data," we will sophisticate our reasoning methods but we need to keep in mind that only part of social interaction has a spatial component.

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AUTHOR QUERIES

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- [AQ1] Please specify appropriate cross reference to chapters in the sentence "As highlighted in several..."
- [AQ2] Please check sentence "Although such links between..." for completeness.
- [AQ3] Please check if you would like to change "mobile people" to "mobile users".
- [AQ4] We have changed Table 14.2 to Figure 1.3 and renumbered the remaining figures in sequential order. Please check.
- [AQ5] Please check if "the audience of this book" should be changed to "the target audience".
- [AQ6] In the sentence "What is relatively new...," please specify what IT framework stands for.
- [AQ7] Please check if "Maximal Information Coefficient" is okay as edited.
- [AQ8] In the sentence "Pathetically, we may claim...," please check the usage of "pathetically" and replace with more appropriate word if necessary.
- [AQ9] Please check if edit to sentence starting "In this respect..." is okay.
- [AQ10] Please provide location for Hey et al. (2009).
- [AQ11] Please check the inserted location in Ho Van et al. (2009).
- [AQ12] Please check the book title and provide publisher and location details for Resch et al. (2011).
- [AQ13] Please provide publisher and location details for Resch et al. (2012a).

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