# Mobile Phones as Ubiquitous Social and Environmental Geo-Sensors

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## ABSTRACT

Mobile and sensor-rich devices such as today's smartphones are increasingly leveraged as ubiquitous mobile geo-sensors that are able to sense their immediate surroundings on site in high spatial and temporal detail. Using those devices, the activity or mobility behavior of mobile phone users is being "sensed" since they leave behind digital traces of their whereabouts when using the mobile network – voluntarily or not. Additionally, people themselves can act as human sensors by providing subjective, geo-referenced "observations" in the form of individual perceptions of, e.g., the weather, thereby complementing calibrated measurements from technical geo-sensor networks. Together with other user-generated and increasingly geo-referenced data and information from a variety of Web 2.0 and social media platforms, this results in vast volumes of geo-data that digitally reflect the dynamics of human behavior (e.g., mobility in urban spaces) and environmental phenomena (e.g., the weather). In this chapter we provide an overview of recent literature, influencing scholars, and future research directions in the context of using mobile phones for social and environmental geo-sensing in order to provide additional insights into the space-time behavior of the underlying geographic phenomena.

## INTRODUCTION

Mobile communication networks have been designed to allow people to communicate wirelessly almost everywhere at all times. Particularly in urban environments such networks are ubiquitous, and so are the mobile communication services they offer. Moreover, communication networks can be seen as higher-level large-scale human behavior sensors (Shoval, 2007), which include in fact hundreds of thousands of mobile in situ geo-sensing components, i.e., the mobile phones carried by their users. The term "in situ", in contrast to "remote", means that the sensor is very close to, or in direct contact with the phenomenon being sensed. For instance, measurements from an air temperature sensor are an example of environmental in situ sensor data. Like this, the user-generated traffic within mobile networks, as well as the geo-referenced social media data published by individuals, can serve as a proxy for the collective human behavior. Such user-generated data are referred to as social in situ sensor data (Sagl & Blaschke, 2014).

Today, smartphones are sensor-rich devices, which are increasingly leveraged as ubiquitous mobile sensors (Khan et al., 2013; Lane et al., 2010) that are able to sense their immediate surroundings on site in high spatial and temporal detail. In fact, people themselves can act as human sensors and provide subjective "observations" in the form of individual perceptions. Such perceptions are increasingly shared by people voluntarily as geographic information on diverse Web 2.0 and social media platforms (e.g., geo-tagged pictures and text on Twitter, Instagram, etc.) via their mobile phones and a mobile network. Such human sensor data can complement calibrated electronic sensor measurements from geo-sensor networks, e.g., for environmental monitoring.

The resulting vast volumes of social and environmental in situ sensor data digitally reflect, to some degree, the spatial and temporal dynamics of human behavior and environmental phenomena, for instance large-scale activity and mobility in urban spaces or objective measures or subjective observations of weather conditions). Furthermore, the consolidation of these highly diverse data on a common space-time basis enables further analyses. The results of such analyses can potentially shed new light on local and short-term environment-human interaction aspects, for instance, the relationships between weather conditions and collective human behavior.

In this chapter, we illustrate the use of mobile phones as ubiquitous social and environmental geo-sensors in order to provide additional insights into the space-time behavior of the underlying geographic phenomena. We focus on investigating human and environmental dynamics, and potential human-environmental relationships. Since such dynamics inherently comprise both a temporal and a geo-spatial component, we herein underpin the added value of integrating interdisciplinary methods linked with Geographic Information Science (GIScience) theory and Applied Geoinformatics.

In the following sections we start with providing a brief overview of the intellectual history in that research area including influencing scholars and institutions. In the main part we elaborate on the current scientific knowledge of three concrete research areas: human-centered data acquisition, space-time patterns of human behavior, and relationships of human behavior in the environmental context. Finally, we provide a conclusion and future research directions related to the overarching context of investigating human and environmental dynamics based on diverse human and technical in situ sensor data.

## OVERVIEW OF THE INTELLECTUAL HISTORY

In this chapter, we put emphasis on the geo-spatial and temporal components of mobile phone data acquisition and data analysis. We focus on the following three concrete research areas:

- Human-centered data acquisition using mobile phones
- Space-time patterns of human behavior derived from mobile phone data
- Exploring human behavior in the environmental context

As a result from deficient data availability and the fast rise of smartphone penetration, new **human-centered approaches for data acquisition** are currently investigated. The interaction with social media such as Twitter, Instagram, Facebook, etc. is increasingly happening on mobile devices (Perreault & Ruths, 2011), thereby generating vast amounts of Volunteered Geographic Information (VGI) (Goodchild, 2009; Goodchild, 2007a). Data from mobile networks and social media thus reflect, to some degree, the dynamics in social environments. Additionally, the concept of "People as Sensors" (Resch, 2013) allows people to share their individual perceptions as subjective "measurements" of, e.g., air quality, the weather, or even their situational emotional feeling via their mobile phones (Resch et al., in press). Like this, the gathered observations complement measurements from technical sensor networks. This is also underpinned by Sarah Elwood who discusses societal implications of neogeography and the "geo-spatial web" and tries to define future research avenues through an extensive review of early literature in the field (Elwood, 2008a, 2008b, 2010).

Research in the field of urban social dynamics and **human behavior patterns** based on mobile phone data has been intensively conducted by the MIT's SENSEable City Lab, Boston (USA), and partner institutions, with several pioneering and currently leading scholars (Calabrese et al., 2013; Calabrese et al., 2011c; Di Lorenzo & Calabrese, 2011; Krings et al., 2009; Quercia, 2010;

Ratti et al., 2006; Ratti et al., 2007; Ratti et al., 2010). Recent examples of urban social dynamics and human behavior patterns are shown in Real-Time Rome (Calabrese et al., 2011a) or LIVE Singapore! (Kloeckl et al., 2012). In the domain of formal mathematical modeling, i.e., deriving general laws of human behavior from vast volumes of mobile phone data, the most influencing scholars are, e.g., Barabási (2005), González and Barabási (2007), Onnela et al. (2007), González et al. (2008), Candia et al. (2008), Simini et al. (2012). One important geographic location for that pioneering research is the Center for Complex Network Research (CCNR), Northeastern University, Boston (USA).

Understanding the complex **interactions between the environment and humans** and the interactions' inherent dynamics is a multidisciplinary challenge. Herein we summarize recent approaches that explore human-environment interactions based on social and environmental sensor data. We focus on the spatial and temporal components of the underlying, typically geographic phenomenon. Since such approaches are rarely documented in scientific literature yet, it is difficult to name influencing scholars or institutions. From a more global and long-term perspective, the environmental and climatic context has certain associations to large-scale human behavior. For instance, researchers have explored the association of El Niño/Southern Oscillation (ENSO) with civil conflicts (Hsiang et al., 2011), or climate change with large-scale mobility and migration (McLeman & Hunter, 2010; Tacoli, 2009). In contrast to these temporal and spatial scale levels, we focus on the operational scale of a city. We demonstrate how ubiquitous technologies such as the mobile phone network and advanced sensing methods, which are needed for information extraction (Hancke et al., 2013), can support this purpose. Furthermore, based such human and technical sensor data, we show examples on how novel analysis methods can be used explore the collective behavior of people in diverse contexts such as the weather.

## CURRENT SCIENTIFIC KNOWLEDGE

Following the brief overview of intellectual history, we highlight the use of mobile phones as ubiquitous sensors for investigating human and environmental dynamics. We start with innovative concepts and methods for human-centered data acquisition using mobile phones. Then, we show methods for deriving spatio-temporal human behavior patterns from mobile phone usage. The final sub-section focuses on exploring some aspects of environment-human interactions in both space and time based on mobile phone data and weather data. These three areas are addressed from a GIScience/Geoinformatics perspective.

### Human-centered Data Acquisition using Mobile Phones

Ubiquitous sensor networks can assist in decision-making in near real-time in a variety of application areas such as public safety, traffic management, environmental monitoring or in public health (Resch et al., 2010a; Sneha & Varshney, 2009). Yet, analyzing and monitoring our surroundings in near real-time is still a major challenge due to sparsely available data sources. As a result from this deficiency, coupled with the fast rise of mobile phones, a number of researchers have started to investigate alternative methods for generating real-time data relevant for decision-making processes. Recent efforts have been taken by OpenSignal (Overeem et al., 2013), On Line Disaster Response Community (Laituri & Kodrich, 2008), CenceMe (Miluzzo et al., 2008) or Near Future Laboratory (Girardin et al., 2008). In scientific literature, we see a number of human-centered sensing approaches that can be summarized in three main concepts: People as Sensors, Collective Sensing and Citizen Science. This sub-section presents a clear disambiguation between these concepts.

**"People as Sensors"** defines a sensing model, in which measurements are not only taken by calibrated hardware sensors, but in which also humans can contribute their subjective “measurements” such as their individual sensations, current perceptions or personal observations. That way, people act as non-technical sensors with contextual intelligence and comprehensive knowledge. Measurements are not created absolutely reproducibly by calibrated sensors, but through personal and subjective observations. Such observations could be air quality impressions, street damages, weather observations, or statements on public safety, submitted via dedicated mobile or web applications. A vibrant real-world example is WAZE (WAZE 2014), a smartphone app allowing people to send their personal traffic reports, which are directly used in other persons’ routing requests. These human sensors can thus complement – or in some cases even replace – specialized and expensive sensor networks. Throughout recent literature, the term “People as Sensors” is used interchangeably with “Citizens as Sensors” (Goodchild, 2007a, 2007b) or “Humans as Sensors” (Forrest, 2010).

The central advantage of such human-centered data acquisition approaches is that no cost-intensive physical sensor networks have to be deployed, but people can use their every day’s devices (smartphones, desktop computers, tablet PCs etc.) to enter their observations into a specialized (mobile) application or data warehouse. The essential drawbacks of the People of Sensors concept are limited comparability and interpretability of the “sensed” data. As semantics research has shown, academic solutions cannot be imposed on specific communities. Hence, other semantic models have to be found to extract information from human observations.

One example, in which this kind of user-generated and volunteered data was of invaluable importance, was the earthquake including the following tsunami in Japan in March 2011. In this case, the Tweet-o-Meter (UCL Centre For Advanced Spatial Analysis, 2012) application has been used to find anomalies in Twitter activity. Right after the earthquake, people started to post status reports, video streams, and conditions of destroyed houses and cities, which could be interpreted in near real-time as an indicator for an extraordinary event. Furthermore, information could be semantically extracted from personal comments and posts. Similar approaches have been used during the typhoon Haiyan (Cranmer & Biddinger, 2014; Merin et al., 2014; Reimer et al., 2014).
A concept related to People as Sensors is Participatory Sensing, in which a number of persons with a common goal in a geographically limited area contribute geo-referenced data via their end user devices such as smartphones (Zacharias, 2012). From this definition it is evident that the term Participatory Sensing is highly similar to People as Sensors, but its definition is a little more restricted in terms of input devices, data acquisition and information processing.

Second, we are currently witnessing a fast rise of **Collective Sensing** approaches. This methodology tries not to exploit a single person’s measurements and data. Thus, it is similar to User-generated Content (UGC) based and crowd-sourcing approaches. However, Collective Sensing analyses aggregated and anonymized data coming from collective networks, such as Flickr, Twitter, Foursquare or the mobile phone network. Like this, we can gain a coarse picture of the situation in our environment without involving personal data of single persons.
In contrast to People as Sensors, Collective Sensing is an infrastructure-based approach, which tries to leverage existing Information and Communications Technology (ICT) networks to generate contextual information. Unlike smartphone-based or specialized web apps, which examine single input data sets, Collective Sensing holistically analyses events and processes in a network. For instance, increased traffic in the mobile phone network might be an indicator for the presence of a dense crowd of people (Reades et al., 2007). This information is generated without having to use a single person’s data and their personal details.

Finally, the term **Citizen Science** plays a key role in the context of People as Sensors. Citizen Science basically states that “through the use of sensors paired with personal mobile phones, everyday people are invited to participate in collecting and sharing measurements of their everyday environment that matter to them" (Paulos et al., 2008). In other words, citizens augment their role, becoming agents of change by uncovering, visualizing, and sharing near real-time measurements from their own everyday environment by exploiting and elevating their expertise and their personal, local experiences. An example for promoting the Citizen Science concept is the "Citizen Science – Community Involvement Today and in the Future" grant program by the US Environmental Protection Agency (EPA) (US EPA, 2014). This program aims to encourage individuals and community groups in New York City to collect information on air and water pollution in their communities, and seek solutions to environmental and public health problems.

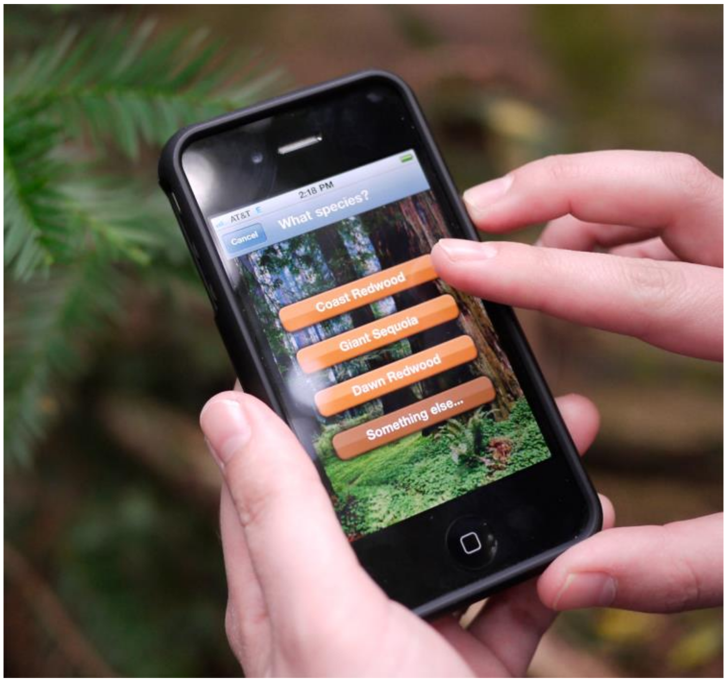


*Figure 1: Redwood Watch Application for Forest Monitoring. (Save the Redwoods League, 2014)*

In consequence, researchers hope that public understandings of science and environmental issues will be improved and can have access to larger and more detailed data sets coupled with local knowledge. This access to environmental data of the city also becomes a tool to raise the citizen awareness of the state of their environment. Figure 1 shows the "Redwood Watch" location-based application, which exploits Citizen Science to predict the growth of redwood forests (Save the Redwoods League, 2014).

Table 1 summarizes the comparison of the discussed concepts of People as Sensors, Collective Sensing and Citizen Science according to the following criteria.

- *Voluntary/Involuntary*: whether contributing people voluntarily (dedicatedly) share their data for further (geo-spatial) analysis or decision-making
- *Content*: type of data, which are contributed
- *A Priori Knowledge*: required knowledge of the user
- *Contextual Data*: whether the contributed data contain contextual intelligence, for instance a person's local knowledge
- *Reliability*: quality level of the generated data and contributors' trustworthiness
- *Analyzed Datasets*: whether single (individual) datasets are analyzed or spatially and temporally aggregated (anonymized) data are used
- *Specific Infrastructure*: whether additional dedicated infrastructure is necessary to collect data

| | People as Sensors | Collective Sensing | Citizen Science |
|---|---|---|---|
| **Voluntary/Involuntary** | Voluntary | Involuntary | Voluntary |
| **Content** | Layman Observations | Raw geo-data (images, tags, ...) | Semi-professional Observations |
| **A Priori Knowledge** | Medium | Low/None | High |
| **Contextual Data** | Yes | Yes | Yes |
| **Reliability** | Medium | Mediocre | Good |
| **Analysed Datasets** | Individual | Aggregated | Individual |
| **Specific Infrastructure** | No | No | No |

*Table 1: Comparison of Human-Centric Concepts.*

## Space-time Patterns of Human Behavior derived from Mobile Phone Data

Ubiquitous mobile communication technologies such as the mobile phone network are able to directly or indirectly “sense” some aspects of the human behavior. The digital traces that people continuously leave behind while using the mobile network 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. This has already proved successful in several investigations and is documented in a huge body of scientific literature (Calabrese et al., 2013; Candia et al., 2008; Farrahi & Gatica-Perez, 2011, 2012; González et al., 2008; Hidalgo & Rodriguez-Sickert, 2008; Järv et al., 2014; Khan et al., 2013; Krygsman et al., 2007; Louail et al., 2014; Noulas et al., 2012; Onnela et al., 2007; Ratti et al., 2006; Reades et al., 2009; Rose, 2006; Sagl et al., 2014; Shoval, 2007; Trasarti et al., in press). A **spatial and temporal analysis** of such proxy-data can provide additional insights into the social dimension of inherently complex urban systems. For instance, the analysis results in Sagl et al. (2012b) show that characteristic and exceptional urban mobility patterns can be derived from handovers[1] using a Visual Analytics approach. Such patterns are potentially important for applications such as real-time monitoring of events since the absolute net migration flow between pairs of radio cells can be used for a rough estimation of the number of people on the move.

Recent research has shown that mobile communication profiles including incoming and outgoing voice, text and data communication can be used as proxy for different **collective human activity patterns** (Sagl et al., 2014). For this, the authors focused on the variations in intensity and similarity of collective human activity by analyzing vast volumes of user-generated mobile network traffic data with Geo-Visual Analytics (Geo-VA), Self-Organizing Maps (SOM) and Local Indicators of Spatial Association (LISA). Figure 2 shows the space-time patterns of typical mobile communication in the city of Udine, Northern Italy, of a three month period in 2009. The five different variables tend to exhibit similar patterns: a larger cluster of cells in the center of town is particularly active around noon and after 6 pm again. The second temporal cluster is more elongated for SMSs than phone calls, probably owing to the fact that several public companies or office close their business at night. Such insights can help to better understand the daily “pulse” of urban movements in the city (Sevtsuk & Ratti, 2010), thereby providing additional information for a variety of application domains, e.g., public transportation, event management, urban

[1] A handover refers to the technical process of transferring a mobile communication sessions from one mobile phone antenna to another while the mobile phone user is on the move; handovers are managed by the mobile network’s backend.

planning, etc. In sum, the results show that variations in intensity and similarity of collective human activity patterns correlate with the functional configuration of a city.

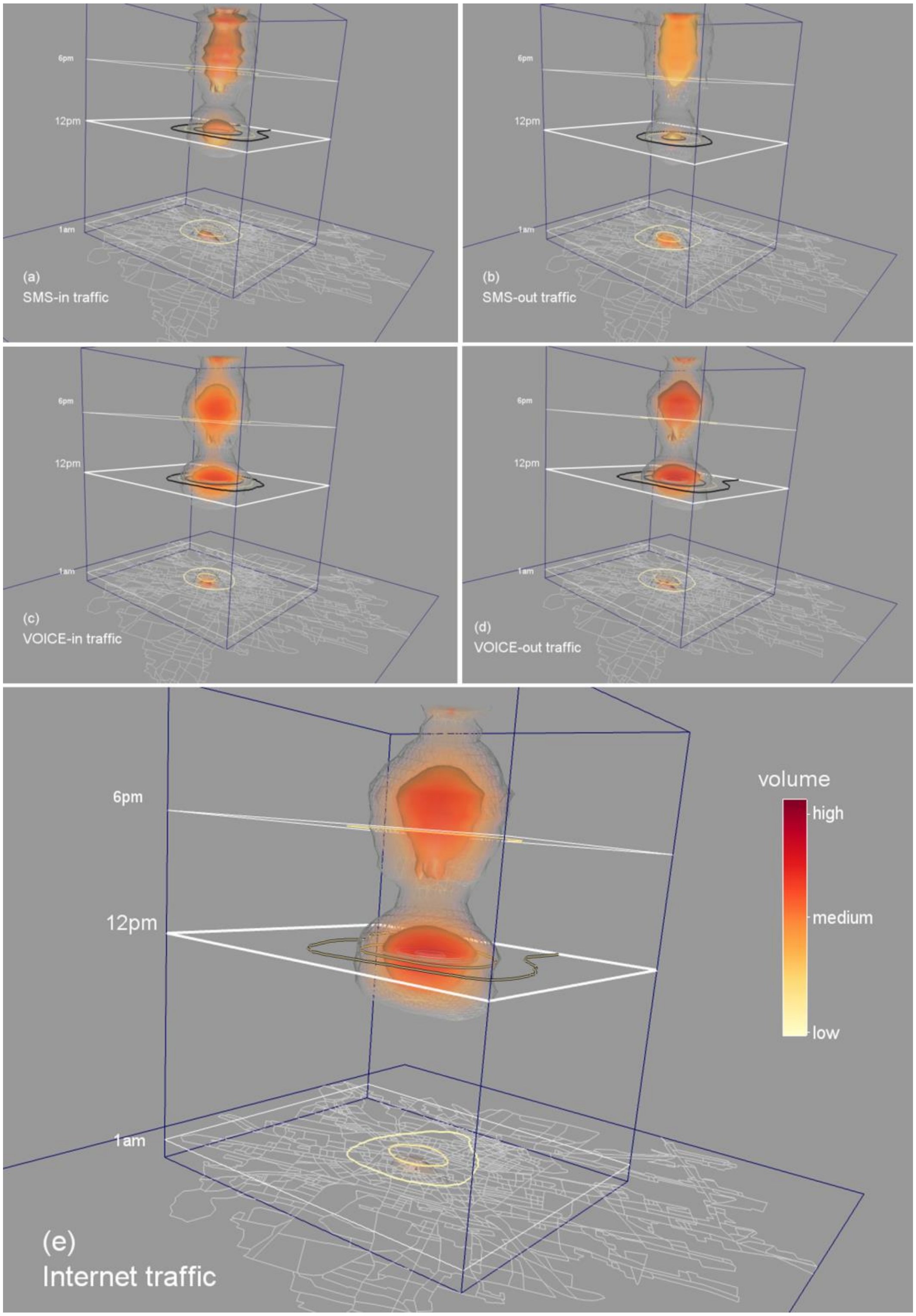


*Figure 2: Space-time visualization of mobile communication patterns: incoming SMS (a), outgoing SMS (b), incoming voice calls (c), outgoing voice calls (d) and overall data traffic (e) (Sagl et al., 2014)*

However, several limitations of such approaches exist. For instance, although mobile phones as ubiquitous in situ sensors can help us understand the spatio-temporal behavior pattern of humans and of groups, they cannot tell us the underlying semantics, i.e. the "why", behind that patterns. Nonetheless, such patterns can be the starting point of further interdisciplinary reasoning to disclose underlying processes.

## Exploring Human Behavior in the Environmental Context

As discussed in the previous section, human behavior patterns can be derived on the basis of user-generated data from ubiquitous mobile in situ geo-sensors – the mobile phones. On the other hand, peoples' living environments are monitored and assessed by a variety of geo-spatial technologies such as remote sensing and especially in situ geo-sensor networks such as weather stations (Blaschke et al., 2011; Hart & Martinez, 2006; Nittel, 2009; Nittel et al., 2008; Resch et al., 2010a; Sagl & Blaschke, 2014). The consolidation of such inherently different environmental and social sensor data on a common space-time basis enables the analysis of potential relationships and associations among the different data sets. This also requires the consideration of potential influencing context factors.

### The Role of Context in Human Behavior Analysis

A variety of diverse context factors influence the human behavior, the environmental context factor is only one of them. Other contexts include mobility (e.g. Calabrese et al., 2011a; Traag et al., 2011), activity (Girardin et al., 2009; Järv et al., 2014; Reades et al., 2009), and social interactivity ( e.g. Calabrese et al., 2011b; Ratti et al., 2010). Human activity patterns of both individuals (Phithakkitnukoon et al., 2010) and communities (Sevtsuk & Ratti, 2010) have been evaluated in the context of urban planning (Becker et al., 2011; Reades et al., 2009), or transportation (Di Lorenzo & Calabrese, 2011). In the context of scale, the human-city interaction system developed by Martino et al. (Martino et al., 2010) provides an interactive visualization of human movements across multiple temporal and spatial scales. Calabrese et al. (2010) consider the context of social events and demonstrate that residents are more attracted to events if the events take place close to the residents' home location. Phithakkitnukoon et al. (2010) found out that specific daily patterns of human activity strongly correlate with certain geographic areas that share a common characteristic context, for instance shopping or eating. From such examples, it can be concluded that the respective context should be taken into account when analyzing human behavior – however, the environmental context has rarely been considered.

### Correlating Weather and Human Behavior based on Social and Environmental Sensor Data

The relationships between the weather and human behavior are multifaceted. For instance, the combination of some meteorological variables such as air temperature, solar radiation, relative humidity, or a combination of these can effect peoples' comfort conditions in outdoor urban spaces (Stathopoulos et al., 2004), poor or extreme weather conditions influence peoples physical activity (Tucker & Gilliland, 2007), etc. Vice versa, significant changes in the collective human mobility behavior can be linked with changes in the intensity of use and the choice of the transport vehicle (e.g. car, bus, train etc.). The vehicles' emissions influence, e.g., the air quality along streets at different times (Nicolopoulou-Stamati et al., 2005). Further, as we experience in our daily live, certain weather conditions such as low pressure systems with heavy rainfall obviously have a certain impact on our behavior. Only a few approaches exist that explicitly address weather as the environmental context and explore potential relationships and interaction between the weather and the human behavior on an urban scale in both space and time. Moreover, any kind of methodology that allows for quantifying such potential relationships can hardly be found in scientific literature.

Sagl et al. (2011) introduced an approach to provide additional insights into some instantaneous interactions between people and the weather. The weather can be seen as a higher-level phenomenon, a conglomerate that comprises several meteorological variables including air temperature, rainfall, air pressure, relative humidity, solar radiation, wind direction and speed, etc. So, instead of considering individual variables, the authors derived some basic weather conditions from longitudinal data of such meteorological variables using dimension reduction methods such as Exploratory Factor Analysis. Those basic weather conditions were then correlated with aggregated mobile phone network traffic, which served as a proxy for the collective human behavior, using frequency domain analysis methods in order to explore periodic patterns. This approach has then been significantly expanded to a more advanced **context-aware analysis** approach in Sagl et al. (2012a). This context-aware analysis approach integrates interdisciplinary analysis methods which are linked with GIScience theory. This composition allows for analyzing one geographic phenomenon in the context of another, e.g., exploring collective human mobility in the context of the weather. Moreover, it allows for quantifying environment-human relationship aspects by the use of a novel statistic, the Maximal Correlation Coefficient MIC (Reshef et al., 2011), that measures the dependence of two variables. In the case study performed in Sagl et al. (2012a), the two variables were a time period of “adverse weather conditions” and “unusual mobile network traffic” – the former refers to weather conditions dominated by rainfall and relatively low air temperature, the latter to the difference between average and actual mobile phone traffic intensity.

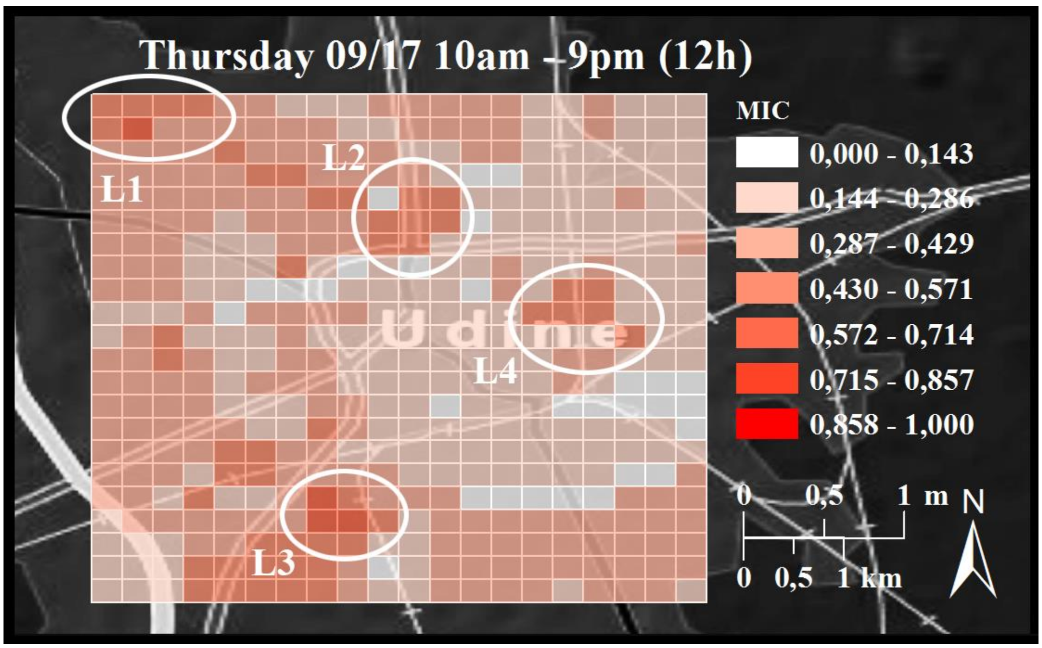


*Figure 3: Spatial Pattern of Potential Environment-Human Relationships – Correlation of Unusual Human Behavior and Adverse Weather Conditions using the Maximal Information Coefficient MIC (modified from Sagl et al., 2012a)*

Figure 3 shows the case study test area, the city of Udine in Northern Italy. The given adverse weather period covers almost only business hours and shows relatively weak relationships in the city center (MIC ≈ 0.2) as compared to the periphery. This could be due to the strength of the ongoing business and its considerable independence from weather conditions – people need to work in all weather. Furthermore, the authors identified four locations L1 to L4: L1 with $0.46 \leq$ MIC $\leq 0.65$ is mainly dedicated to university education, whereas the outdoor area with a MIC of 0.65 is commonly used by students to meet, learn, study, socialize etc. However, according to

(Università degli studi di Udine, 2012), the new academic year had not had officially started. A comprehensible explanation of that relationship thus remains pending; L2 is dominated by a traffic junction of the busy main road entering the city from the north and the ring road. The fair MIC of 0.46 could thus be associated with problems in road traffic flow due to bad weather conditions; L3 and L4 with $0.46 \leq \text{MIC} \leq 0.65$ is mostly residential. From these analysis results it can be concluded that the geo-spatial pattern of that MIC statistic correlates with the functional configuration of the test area (Figure 3).

Phithakkitnukoon et al. (2012) explored the effects of the weather on mobile social interactions based on individual mobile phone data records of more than 20,000 users for the period of a full year in Lisbon, Portugal. The authors correlated different proxies of social behavior such as phone call duration, number and strength of connected social ties with individual meteorological variables including air temperature, relative humidity, air pressure, and wind speed. They found out that, for instance, people tend to call longer when the air temperatures is low and the air pressure is high, and that people tend to communicate with fewer social ties when the weather conditions are uncomfortable. However, since their results are global with respect to the study region and the time period, the spatio-temporal dynamics inherent in the data sets – and probably within the relationships between weather and social interaction too – were neglected. This approach has been expanded in Horanont T. et al. (2013) and tested in another study area (Tokyo). In that study, the authors inferred the most probable activity of each individual for each hour of a typical day. The study is based on anonymized GPS locations from individual mobile phone users and the national phone directory, which served as a reference for building categories of places that can be associated to people's activities (e.g., eateries, retail, education, etc.). These daily activity patterns were then correlated with meteorological data (air temperature, rainfall, and wind speed) from six different weather stations in the area in order to show that each meteorological variable has variable impact in different administrative subdivisions of the study area. Furthermore, some relationships between the impacts of air temperature, rain, and wind on the people's accessibility to public transportation, especially train stations, have been found.

However, we need to be aware that the relationship between the weather and collective human activity is highly complex and multifaceted. Several spatio-temporal aspects of environment-human relationships are yet unknown. For instance, where and when certain weather conditions such as heavy rainfall or extraordinary hot days influence people's activity and mobility. Thus, the data sample and analysis methods used herein are an attempt to reveal and assess some of these aspects, which are, at least, carefully examined approximations. Thus, a closer integration of interdisciplinary reasoning methods and expertise from diverse domains such as sociology or urban planning is necessary to release the full potential of such approaches.

It can be concluded nonetheless that such approaches successfully demonstrate that the advanced analysis of environmental and social in situ sensor data using interdisciplinary methods can provide additional insights into inherently complex systems. This allows for a better understanding of some aspects of environment-human interactions, underlying real-world geographic processes and their potential interrelationships.

**Towards a more Holistic Understanding of Human-Environment Interactions**

From a more conceptual point of view, a holistic understanding of geographic phenomena and geographic processes can be enabled through a more general analysis and monitoring framework. Such a framework need to consolidate data from a vast variety of sensors and sensing systems, from mobile phones and social media to environmental monitoring networks and weather stations to remote sensing and satellite imagery.

Montgomery and Mundt (2010) describe a comprehensive but rather technical framework of how to combine and integrate various sensor data into a common platform on an almost global level. At a regional or even local level, Blaschke et al. (2011, p1762) claim: “What is really needed is a better understanding of human-environmental processes, i.e., direct measures of the impact of human activities on the environment and direct measures of environmental stressors on human functions.”

The **adaptive geo-monitoring framework** (Sagl, 2012), which extends the adaptive monitoring approach (Lindenmayer & Likens, 2009) by adding the geo-spatial dimension, introduces one possibility to consider the mutual context-awareness when analyzing and monitoring dynamic geographic phenomena. Therefore, such a framework potentially provides novel capabilities for investigating the spatio-temporal behavior of both physical and social phenomena through ubiquitous sensing and context-aware analysis, thereby enabling a more holistic understanding of human-environment interactions.

## CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In this chapter we provided an overview of the field of social and environmental geo-sensing using mobile phones in the overarching context of investigating human and environmental dynamics. We presented several influencing scholars and institutions in the context of that field. Further, we elaborated on three related research areas: human-centered data acquisition using mobile phones, space-time patterns of human behavior derived from mobile phone data, and exploring human behavior in the environmental context. Within these three areas, we emphasized the inherent spatial and temporal characteristics from a GIScience/Geoinformatics perspective. From a broader view point, the approaches and research outcomes presented herein thus facilitates the concept of a “Digital Earth” (Goodchild et al., 2012; Gore, 1998) and the metaphor of an “Electronic Skin” of planet earth (Gross, 1999), which both emphasize the technological innovations that provide unprecedented amount of digital data and information reflecting real-world phenomena and processes in exceptional spatial and temporal detail.

However, we are aware that we had only investigated isolated aspects of social and environmental dynamics, specifically in the sub-section on exploring the human behavior in the environmental context. Without venturing into a debate of environmental determinism, we state that many factors influence the collective human behavior, and the weather is certainly only one of these factors. The case studies described demonstrate that human-environmental relationships can be investigated, in principle, based on diverse “sensor data”. We need to be reminded that such data, although increasingly vast in volumes and available even in real-time, are still “just” digital samples, and thus proxies of the phenomena or processes of interest – which are typically much more complex. Further, to what degree the results explain causalities will depend on interdisciplinary expert knowledge, as well as on the field of application.

Hence, a number of challenges remain for future research and deeper investigations of human and environmental dynamics – several of them go beyond the use of mobile phones as ubiquitous mobile geo-sensors:

- The different nature of user-generated data results in differences in terms of **representativeness and semantic expressiveness:** The user-generated mobile network traffic represents a relatively large proportion of the population across social classes. However, these data are typically lacking content. For instance, the number of text messages sent or received might be logged, rather than the text itself; or the number and duration of voice calls might be logged, rather than the topic of the talk itself. This is in strong contrast to social media data and VGI. These data are typically generated by a rather specific sub-group of the population, and explicitly contain content of some semantic value.

- Some phenomena are sensed directly and for a predefined reason while others are sensed indirectly or possibly not even intended to be sensed. For instance, certain quality criteria of an air temperature sensor ought to be documented in its technical specification. So, the sensor's **measurement accuracy** is reliable to that degree. In contrast, the user-generated traffic in mobile networks is managed by the network's backend in order to enable mobile people to communicate wirelessly everywhere at any time. Just as a by-product, the log files from such a backend can reflect the human behavior patterns of millions of mobile users. In other words, the spatio-temporal dynamics of the phenomena of interest can either be "guaranteed" (in the case of the air temperature) or fairly be assumed (in the case of human behavior) to be reflected in the sensor data. As a result, the sensor data's context and semantics can vary considerably. Thus, an interdisciplinary challenge is the extraction of significant spatio-temporal information from such diverse sensor data that are different by nature and comprise differences in semantic expressiveness.
- A connected methodological issue in the field of semantics is **representativeness in VGI**. This has to be tackled by a combined bottom-up/top-down approach. In bottom-up approaches, user groups and communities define their own semantic objects and interrelations between these in separate taxonomies. In contrast, top-down approaches try to define semantic rules and ontological relations as generically as possible – mostly before actual applications exist and decoupled from real-world use cases. Only the combination of those approaches can result in trans-domain semantic models, which are linked via object relations.
- The requirement of high-quality information seems to be self-evident, but has not been tackled thoroughly for real-time geo-sensor networks and People as Sensors based approaches. The subjectivity of human "measurements" naturally raises the question of **trustworthiness** of these data in terms of data quality. As discussed above, this results in uncertainty in the observation data. Thus, automated quality assurance mechanisms need to be developed for uncertainty estimation, dynamic error detection, correction and prevention. Different approaches are in development, e.g., Complex Event Processing (CEP) (Resch et al., 2010b) for error detection, standardization efforts for representing uncertainty in sensor data (e.g. Uncertainty Markup Language - UncertML) (Williams, 2008), or proprietary profiles to define validity ranges for particular observations. Such issues need to be solved in order to ensure reliability of both technical and human sensor data.

Another pressing question is: how can we **preserve people's privacy** when dealing with user-generated data and information, and partly sensitive personal data, in the context of mobile phones as ubiquitous in situ geo-sensors? In terms of privacy, the claim might arise that we need to be aware of our personal and private data before we share them. This also raises the need to discuss the concept of U-VGI, i.e. Un-Volunteered Geographic Information, in contrast to VGI (Resch, 2013). For instance, Collective Sensing approaches exploit anonymized data from digital networks (e.g. by deducing crowd movements from traffic distribution in the cell phone network) even though people have not intended to share their data in this way.

As mobile phone data and human sensor data are individual oftentimes sensitive, **legal frameworks** have to be developed on national, trans-national and global levels to protect those personal data. The largest limiting factor in this regard is the varying interpretation of 'privacy' in different parts of the world. For instance, privacy can be traded like an economic good by its owner in the USA, whereas it is protected by law in the European Union. This means that supra-national legislation bodies and initiatives are called upon to set up appropriate world-wide regulations. As shown in Figure 4, legislation and governments play a highly different role in these two settings.

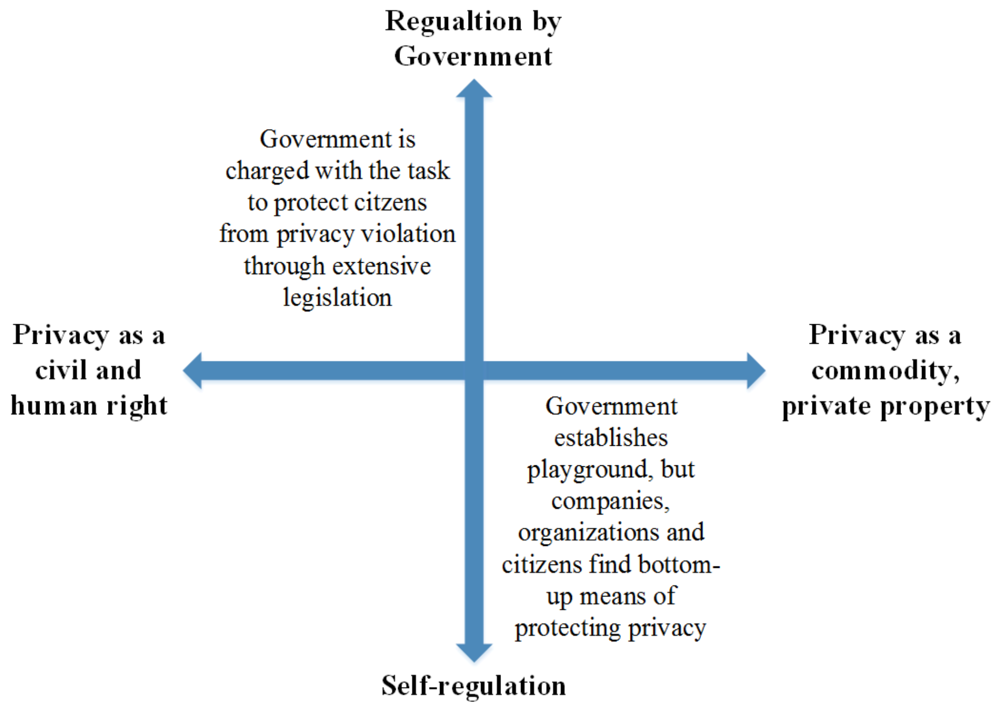


*Figure 4: (about here) Understanding of Privacy vs. the Government's Role in Regulation.*

This also includes the critical question of **data ownership**. Shall they be owned by data producers, i.e., the citizens or a mobile phone network operator? Or rather the institution that hosts a system in order to collect data? Or the data providers? Furthermore, if sensitive data is analyzed to produce anonymized information layers, who is responsible if decisions that are based on this information are wrong due to lacking quality of the base data? In conclusion, the issues of privacy, data ownership, accessibility, integrity and liability have to be tackled thoroughly all at once and not separately from each other.

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## RECOMMENDED READINGS

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## KEY TERMS AND DEFINITIONS

**Ubiquitous Sensing**: Ubiquitous sensing, or ubiquitous 'geo-'sensing to emphasize the spatial dimension, refers to the wide variety of omnipresent technical and human sensors and geo-sensor networks and their ability to probe geographic phenomena even in real time (Sagl et al. 2012a, Sagl & Blaschke 2014).

**Spatio-temporal Analysis**: Generally speaking, the broad spectrum of Spatio-temporal Analysis investigates geographic space and time in order to extract meaningful spatial and temporal information.

**People as Sensors**: "People as Sensors defines a measurement model, in which measurements are not only taken by calibrated hardware sensors, but in which also humans can contribute their subjective 'measurements' such as their individual sensations, current perceptions or personal observations" (Resch 2012, p. 392).

**Volunteered Geographic Information**: Volunteered Geographic Information (VGI) refers to "the widespread engagement of large numbers of private citizens, often with little in the way of formal qualifications, in the creation of geographic information, a function that for centuries has been reserved to official agencies. They are largely untrained and their actions are almost always voluntary, and the results may or may not be accurate. But collectively, they represent a dramatic innovation that will certainly have profound impacts on geographic information systems (GIS) and more generally on the discipline of geography and its relationship to the general public" (Goodchild 2007a, p. 212).

**Environment-Human Interaction**: Environment-Human Interaction herein refers to potential interactions between the natural environment and the human, for instance, the influence of certain weather conditions on people's mobility, or, vice versa, the influence of car traffic on air quality (Sagl et al. 2012a).

**Context-Awareness**: Context-Awareness herein refers to the analysis of one geographic phenomenon in the context of another, for instance, the analysis of collective human mobility in the context of certain weather conditions. Thus, Context-Awareness is strongly linked to Environment-Human Interaction (Sagl et al. 2012a, Sagl & Blaschke 2014).