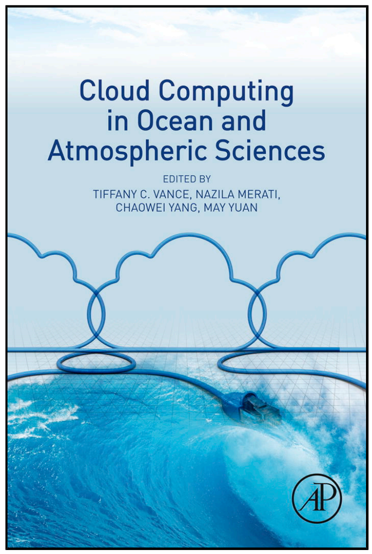

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CHAPTER 15

Usage of Social Media and Cloud Computing During Natural Hazards

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INTRODUCTION

Natural hazards are severe events that pose a threat to the sustainment and survival of our society. Every year extreme weather and climate events, such as typhoons, floods, tornadoes, hurricanes, volcanic eruptions, earthquakes, heat waves, droughts, or landslides, claim thousands of lives, cause billions of dollars of damage to property (Smith and Matthews, 2015) and severely impact the environment worldwide (Velev and Zlateva, 2012). Natural hazards become disasters when they cause extensive damage, casualties, and disruption (Vasilescu et al., 2008). Disasters have been increasing in both frequency and severity in the 21st century because of climate change, increasing population, and reliance on aging infrastructure. Recently, major events have caused havoc around the world, such as the 2015 earthquakes in Nepal, the 2015 heat wave in India, the 2011 tsunami in Japan, the 2010 earthquake in Haiti, and the extremely cold winter of 2014/2015 in the United States and in Europe.

Most disasters occur rapidly with little or no warning, and therefore are often extremely difficult to predict. However, effective actions and management strategies can mitigate the potential effects. For several decades, emergency managers and disaster researchers have typically relied on a four-phase categorization (mitigation, preparedness, response, and recovery) to understand and manage disasters (Neal, 1997; Warfield, 2008):

- Mitigation: Concerns the long-term measures or activities to prevent future disasters or minimize their effects. Examples include any action that prevents a disaster, reduces the chance of a disaster happening, or

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reduces the damaging effects of a disaster, e.g., building levies, elevating a building for a potential hurricane, or public education.

- Preparedness: Plans how to respond a disaster. Examples include developing preparedness plans, providing emergency exercises/training, and deploying early warning systems.
- Response: Minimizes the hazards created by a disaster. Examples include search and rescue, and emergency relief.
- Recovery: Restores the community to normal. Typical activities during this phase include providing temporary housing, grants, and medical care.

The four disaster management phases do not always, or even generally, occur in isolation or in this precise order. Often phases of the cycle overlap and the length of each phase greatly depends on the severity of the disaster (Warfield, 2008). However, the four-phase categorization serves as a time reference for practitioners to predict challenges and damage, prioritize functions, and streamline activities during the course of disaster management (U.S. Department of Education, 2010; FEMA, 1998). It also provides a common framework for researchers to organize, compare, and share their research findings.

When natural hazards occur, disaster management and coordination rely on the availability of timely actionable information. Crucial information includes an assessment of damage and available resources that can be used for planning evacuation and rescue operations to minimize the losses and save lives. This information augments our understanding of the overall disaster situation, and facilitates the decision-making toward a better response strategy. Such information is referred as "situational awareness," i.e., an individually as well as socially cognitive state of understanding "the big picture" during critical situations (Vieweg et al., 2010). However, such information is difficult to obtain because of limitations in data acquisition and techniques in processing the data efficiently in near real time. Additionally, such information may not be effectively disseminated through traditional media channels.

Because of the massive popularity of social media networks and their real-time production of data, these new streams offer new opportunities during emergencies. Social media data are increasingly used during crises. A Red Cross survey in 2012 indicated that 18% of adults, if a call to 911 was unsuccessful, would next turn to social media, whereas 76% expected help to arrive within 3h of posting their need to social sites (American Red Cross, 2012). Social media networks have even become widely used as an intelligent "geo-sensor" network to detect and monitor extreme events or disasters such as earthquakes (Sutton, 2010). The fundamental premise is that human actors in a connected environment, when augmented with ubiquitous mechanical sensory systems, can form the most intelligent sensor web (Sheth et al., 2008). Such intelligent sensor webs have the most realistic implications for operations such as disaster, in which information is the most valuable and hard to obtain asset (Verma et al., 2011;Vieweg et al., 2010). Additionally, it has been widely acknowledged that Humanitarian Aid and Disaster Relief (HA/DR) responders can gain valuable insights and situational awareness by monitoring social media-based feeds from which tactical, actionable data can be mined from text (Ashktorab et al., 2014; Gao et al., 2011; Huang and Xiao, 2015; Imran et al., 2013; Kumar et al., 2011).

Faced with real-time social media streams from a multitude of channels during emergencies, identifying authoritative sources and extracting critical, validated messages information for the public could be quite challenging in a time of crisis. The volume, velocity, and variety of accumulated social media data produce the most compelling demands for computing technologies from big data management to technology infrastructure (Huang and Xu, 2014). For big data management, many nontraditional methodologies such as non-relational and scalable Structure Query Language (NoSQL) are implemented (Nambiar et al., 2014). Meanwhile, to address big data challenges, various types of computational infrastructures are designed, from the traditional cluster and grid computing to the recent development of cloud computing and central processing unit/graphics processing unit (CPU/GPU) heterogeneous computing (Schadt et al., 2010). Specifically, cloud computing has been increasingly viewed as a viable solution to utilize multiple low-profile computing resources to parallelize the analysis of massive data into smaller processes (Huang et al., 2013b).

Similarly, the computational requirements for an operational system that can be deployed for event predictions and subsequent disaster management are very demanding. However, most natural hazards occur very quickly, have immediate impacts, but only last a relatively short period of time. Therefore, it is necessary to support operations by scaling up to enable high-resolution forecasting, big data processing, and massive public access during a crisis, and by scaling down when no events occur to save energy and costs. Cloud computing provides an ideal solution due to its intrinsic capability of providing a large, elastic, and virtualized pool of computational resources which can be scaled up and down according to the needs. The goal of this chapter is to discuss the opportunities and challenges associated with the usage of social media to gain situational awareness during natural disasters, and the feasibility of using cloud computing to build an elastic, resilient, and real-time disaster management system.

SOCIAL MEDIA FOR DISASTER MANAGEMENT

Disaster management aims to reduce or avoid the potential losses from hazards, assure prompt and appropriate assistance to victims of disaster, and achieve rapid and effective recovery (Warfield, 2008). Social media can be used as new sources to redefine situational awareness and assist in the management of various disaster stages.

Social Media Fundamentals

There are a variety of definitions of social media (Cohen, 2011). In general, social media are broadly defined as any online platform or channel for user-generated content. A large number of social media services or Web sites are developed to enable the public to distribute and share different types of content, such as videos, text messages, photos, etc. In this regard, Wiki, WordPress, Sharepoint, and Lithium qualify as social media as do YouTube, Facebook, and Twitter. Based on the content generated and functions provided, social media services are generally categorized into several classes (Nations, 2015):

- Social networking: Interacts by adding friends, commenting on profiles, joining groups and having discussions. Such social network sites can produce, spread, and share relatively short messages, photos, or videos over the Internet at a high speed. These messages can be immediately accessible by the linked groups or friends. Therefore, they are commonly used by the public to post relevant information via microblogs about the disaster, and share their own knowledge about the disaster situation with others, thus contributing the situational awareness. For example, users in the impacted communities can report what they are witnessing and experiencing. Twitter, Facebook, and Google+ belong to this category.
- Social bookmarking: Interacts by tagging Web sites and searching through Web sites bookmarked by other people. Typical examples include Del.icio.us, Blinklist, and Simpy.
- Social news: Interacts by voting for articles and commenting on them. Good examples are Reddit, Propeller, or Digg.
- Social photo and video sharing: Interacts by sharing photos or videos and commenting on user submissions. The most two popular examples are YouTube (videos), and Flickr (photos).
- Wikis: Interacts by adding articles and editing existing articles. In fact, any Web site that invites users to interact with the site and with other visitors falls into this category. Wikipedia is the one of the earliest and popular examples to enable users to create articles and web pages. OpenStreetMap is another example to enable the public to share geographic data and maps.

However, social media more narrowly defined include only channels for user-generated content, as distinguished from platforms, which are referred to as social technologies. According to this definition, for example, YouTube, Facebook, and Twitter are social media, and WordPress, Sharepoint, and Wikis are social technologies (Cohen, 2011). Although both channels for user-generated content and social technologies can be leveraged to support disaster management in many different ways, they have different functions and usages for disaster management. For this reason, this chapter adopts the narrow definition.

Opportunities

Social media are widely used during natural disasters as a news source and tool by both the public and emergency service agencies. For example, citizens normally use social media in four different ways (Velev and Zlateva, 2012): (1) To communicate with family and friends. Social network sites provide a bridge to connect with family members between affected and unaffected communities or areas (or within affected communities for situation updates and planning responses). This is the most popular use. (2) To update and share critical information between each other such as road closures, power outages, fires, accidents, and other related damage. (3) To gain situational awareness. In a number of cases citizens rely less and less on authority communication, especially through traditional channels (television, radio, or phone). Finally, (4) to assist in service access, citizens use social media channels to provide each other with ways and means to contact different services they may need after a crisis. On the other hand, emergency service agencies are utilizing social media to instantly alert emergency warnings to the public, and collect feedback and updates from the public users.

In fact, social media are useful in different disaster stages (Velev and Zlateva, 2012). Before a disaster, social media can help people better prepare and understand which organizations will help their communities. After the disaster, social media help bring the community together to discuss issues, share information, coordinate recovery efforts, and communicate information about aid. As we discussed earlier, social media can play a more significant role by helping users communicate and share information in real time directly to their families, reporters, volunteer organizations, and other residents during a disaster. In particular, research and reviews of different cases have identified the following benefits of social media and social technologies in emergency response (Prentice et al., 2008; Yates and Paquette, 2011):

- Near real-time: Social media (including social network sites and social technologies) are essentially real-time offering unique strengths as a data source, methods, and tools for the sharing of information in emergencies (Prentice et al., 2008). Previously, methodologies such as phone calls, direct observation, or personal interview are commonly practiced by disaster responders and damage evaluators to gain situational awareness and investigate impacted population during a disaster. However, these data collection methods are time-consuming and laborious in processing the data. Social media data, however, can provide near "real-time" information for the emergency managers to make effective decisions through multiple stages of the disaster management.
- Facilitates knowledge sharing: social media facilitate better knowledge sharing between communities and organizations. Connections can be made among individuals without limitations introduced by bureaucratic boundaries (Yates and Paquette, 2011).
- Provides broad access: Internet-connected devices allow sharing the information in real time (Yates and Paquette, 2011).
- Offers contextual cues for understanding a given perspective: Typically, when people engage in a conversation about the larger context of a disaster, they tend to be clearer about the situation (Yates and Paquette, 2011).
- Conversational, discussion-based style: Social media sites can provide a platform for discussion and feedback from those who care the most and have the most lasting impact on the story of the disaster (Prentice et al., 2008).
- Limits restrictions and maintains strengths of "old media": Social media also bypass the deadlines and restrictions placed on "old media" (Prentice et al., 2008).
- Two-way medium: Organizations can respond directly to comments and feedbacks posted on blogs, Twitter, or Facebook, or even leverage other social technologies such as YouTube to distribute timely and accurate information directly to those concerned (Prentice et al., 2008).

State-of-the-Art Work and Practice

Many recent studies have applied social media data to understand various aspects of human behavior, the physical environment, and social phenomena. Studies and applications of using social media for disaster related analysis include following major areas: (1) event detection and sentiment tracking; (2) disaster response and relief coordination; (3) damage assessment; (4) social media message coding during a disaster; and (5) user rank model.

Event Detection and Tracking

The network of social media users is considered a low-cost, effective "geo-sensor" network for contributed information. Twitter, for instance, has more than 190 million registered users, and 55 million Tweets are posted per day. As an example, Asiana Flight 214 from Seoul, Korea, crashed while landing at San Francisco International Airport on July 6, 2013. News of the crash spread quickly on the Internet through social media. With eyewitnesses sending Tweets of their stories, posting images of the plumes of smoke rising above the bay, and uploading video of passengers escaping the burning plane, the event was quickly acknowledged globally.

As a result of the rapid or even immediate availability of information in social networks, the data are widely applied for the detection of significant events. Sakaki et al. (2010), for instance, investigated the real-time interaction of events such as earthquakes and Twitter. Their research produced a probabilistic spatiotemporal model for the target event that can find the center and the trajectory of the event location. Kent and Capello (2013) collected and synthesized user-generated data extracted from multiple social networks during a wildfire. Regression analysis was used to identify relevant demographic characteristics that reflect the portion of the impacted community that will voluntarily contribute meaningful data about the fire. Using Hurricane Irene as example, Mandel et al. (2012) concluded that the number of Twitter messages correlate with the peaks of the event, the level of concern dependent on location and gender, with females being more likely to express concern than males during the crisis.

Disaster Response and Relief

Social media data are real-time in nature, and it has been widely acknowledged that HA/DR responders can gain valuable insights and situational awareness by monitoring and tracking social media streams (Vieweg, 2012). As a result, an active area of research focuses on mining social media data for disaster response and relief (Ashktorab et al., 2014; Gao et al., 2011; Huang and Xiao, 2015; Imran et al., 2013; Kumar et al., 2011; Purohit et al., 2013). Aiming to help HA/DR responders to track, analyze, and monitor Tweets, and to help first responders gain situational awareness immediately after a disaster or crisis, Kumar et al. (2011), for example, presented a tool with data analytical and visualization functionalities, such as near real-time trending, data reduction, and historical review. Similarly, a Twittermining tool, known as Tweedr, was developed to extract actionable information for disaster relief workers during natural disasters (Ashktorab et al., 2014). Gao et al. (2011)

described the advantages and disadvantages of social media applied to disaster relief coordination and discussed the challenges of making such crowdsourcing data a useful tool that can effectively facilitate the relief process in coordination, accuracy, and security. Recent findings also suggest that actionable data can be mined and extracted from social media to help emergency responders act quickly and efficiently. Purohit et al. (2013) presented machine learning methods to automatically identify and match needs and offers communicated via social media for items and services such as shelter, money, clothing, etc.

Damage Assessment

Damage assessment of people, property, and environment, and timely allocation of resources to communities of greatest need, and is paramount for evacuations and disaster relief. Remote sensing is capable of collecting massive amounts of dynamic and geographically distributed spatiotemporal data daily, and therefore often used for disaster assessment. However, despite the quantity of big data available, gaps are often present due to the specific limitations of the instruments or their carrier platforms. Several studies (Schnebele and Cervone, 2013; Schnebele et al., 2014, 2015), have shown how crowdsourced data can be used to augment traditional remote sensing data and methods to estimate flood extent and identify affected roads during a flood disaster. In these works, a variety of nonauthoritative, multisourced data, such as Tweets, geolocated photos from the Google search engine, traffic data from cameras, OpenStreetMap, videos from YouTube, and news, are collected in a transportation infrastructure assessment construct an estimate of the extent of the flood event.

Message Coding

As the messages broadcasted and shared through the social media network are extremely varied, a coding schema is needed to separate the messages into different themes before we can use them to produce a crisis map or extract "actionable data" as information that contributes to situational awareness. During Typhoon Bopha in the Philippines in 2012, volunteers using the PyBossa, a microtasking platform, manually annotated the Tweets into various themes, such as damaged vehicle, flooding, etc., and a crisis map was produced to be used by humanitarian organizations (Meier, 2012). A few attempts (Huang and Xiao, 2015; Vieweg, 2012) have been made to uncover and explain the information exchanged when Twitter users communicate during mass emergencies. Information about casualties and damage, donation efforts, and alerts are more likely to be used and extracted to improve situational awareness during a time-critical event. As a result, messages are typically categorized into these categories. Imran et al. (2013), for instance, extracted Tweets published during a natural disaster into several categories, including caution and advice, casualty and damage, donation and offer, and information source. The content categories (or topics) defined in those studies (Vieweg et al., 2010; Vieweg, 2012; Imran et al., 2013), are very useful to explore and extract the data involved in the disaster response and recovery phases. The content categories (or topics) defined in previous studies (Imran and Castillo, 2015; Vieweg et al., 2010; Vieweg, 2012), however, only consider the "actionable data" involved in the disaster response and recovery phases while ignoring useful information that could be posted before or after a disaster event. Huang and Xiao (2015) made an initial effort by coding social media messages into different categories within various stages of disaster management. Based on the coding schema, a supervised classifier was also trained and used to automatically mine and classify the social media messages posted by Twitter users into these predefined topic categories during various disaster stages.

User Rank Model

Research along this line focuses on identifying Twitter users who contribute to situational awareness. The topic of measuring "contribution" or "influence" within the online social network has been intensively investigated. Cha et al. (2010) examined three metrics of user influence on Twitter, including in degree (the number of people who follow a user), retweets (the number of times others "forward" a user's Tweet), and mentions (the number of times others mention a user's name). They also investigated the dynamics of an individual's influence by topic and over time. The results show that in degree alone reveals very little about the influence of a user. Bakshy et al. (2011) use the size of a diffusion tree, which represents the information diffusion by retweets, to quantify the influence of a Twitter user. Cheong and Cheong (2011) investigated popular and influential Twitter users in the digital social community during several Australian floods. The concept of centrality in social network analysis technique was adopted, and various centrality measures were used to identify the influential users, including local authorities, political personalities, social media volunteers, etc.

Challenges

As with any new technology, there remain many hurdles between current use and optimal exploitation of social media for disaster analysis and management.

Digital Divide

Although these media are used by people of both sexes and an expanding range of ages, it is important to recognize and explore the technology's limitations in reaching at-risk, vulnerable populations. The "digital divide" refers to the gap between those who have and those who do not have access to computers and the Internet (Van Dijk, 2006). An active area of research is focused on exploring the factors that lead to the social inequality in the usage of social media. Witte and Mannon (2010) claimed that marginalized populations often lack or have limited net access in their households, making access to Twitter a socially stratified practice. Livingstone and Helsper (2007) conducted a survey among children and young people, and found that inequalities by age, gender, and socioeconomic status relates to the quality of access to and use of the internet. For example, it was reported that the public under 35 are more likely to participate in social media every or nearly every day (63% vs. 37% for those 35 and over) (American Red Cross, 2012). It was also shown that racial digital divides continue to remain pervasive (Nakamura, 2008), and Twitter is no exception to this.

It has been recognized that certain groups (i.e., low income, low education, and elderly) may lack the tools, skills, and motivations to access social media, and therefore they may be less likely post disaster-relevant information through social media (Xiao et al., 2015). Additionally, certain areas may be severely damaged by the disaster, which result in extremely low participation in social media usage after the disaster. As a result, the situational awareness information extracted from social media data may be biased and can underestimate and mis-locate the needs of the significantly impacted communities. Therefore, the social and spatiotemporal inequality in the usage of social media data must be fully considered when using them to predict damage, investigate impacted populations, and prioritize activities during the course of disaster management by practitioners.

Data Quality

Despite many advantages of social media data, concerns have been raised about their quality (Goodchild and Li, 2012; Oh et al., 2010). The first concern originates from the user and information credibility. It is quite challenging to know whether social media users are who they claim to be or whether the information they share is accurate. For example, during the Haiti earthquake, rumors circulated in Twitter that United Parcel Service (UPS) would "ship any package under 50 pounds to Haiti" or "several airlines would take medical personnel to Haiti free of charge to help with earthquake relief" (Leberecht, 2010). These turned out to be hearsay rather than eyewitness accounts, and subsequently clarified by UPS and airline companies as false information. As a result, Twitter, has been long criticized as it may propagate misinformation, rumors, and, in extreme case, propaganda (Leberecht, 2010). In fact, based on the analysis of credibility of information in Tweets corresponding to 14 high-impact news events of 2011 around the globe, Gupta and Kumaraguru (2012) claim that only "30% of total tweets about an event contained situational information about the event while 14% was spam." In addition, about "17% of total tweets contained situational awareness information that was credible."

Another concern comes from the location reliability. Users with location services enabled on smart mobile devices can post content (e.g., text messages or photos) with locations, which typically are represented as a pair of coordinates (latitude and longitude). The locations along with the place names mentioned in the content text are then used to identify the areas of damaged infrastructure, affected people, evacuation zones, and the communities of great needs of resources. During this process, we rely on the assumption that users will report information about the events (e.g., flooded roads, closure of bridges, shelters, or donation sites) they witnessed and experienced at the exact locations where these events occurred. However, the locations in the time of posting content and locations of event occurred are not necessarily consistent and the supposed locations of greatest needs could be misleading. To address these concerns, other data sources (e.g., uthoritative data and remote sensing data) may be integrated for cross-validation, and crowdsourcing validation procedures can be applied to leverage volunteers for improving quality of these user-generated content.

Big Data

Although scholars and practitioners envisioned the possibilities in utilizing social media for disaster management, the computational hurdle to practically leverage social media data is currently extremely high (Huang and Xu, 2014; Elwood et al., 2012; Manovich, 2011). Social media data present challenges at least in the following four dimensions (Huang and Xu, 2014):

1. There is the huge volume of social media data. For Twitter alone, the number of Tweets reached 400 million per day in March, 2013, and that number is escalating rapidly.
2. There is the enormous velocity of real-time social media data streams. In 2014, 9100 Tweets were posted every second in Twitter.

3. There are the high variety types of social media data content. Text-based Tweets, image-based Flickr photos, or video-based YouTube posts are all telling similar stories using different media.
4. Social media data are assertive and create the trustworthiness or veracity question.

These dimensions are now widely cited as the four V's of big data (Fromm and Bloehdorn, 2014). Although the trustworthiness touches upon nontechnical challenges, the other three challenges put more demands on innovative computational solutions (Agrawal et al., 2011). To address such challenge, new computing infrastructure and geovisualization tools should be leveraged to support the exploration of social media in space and time (Roth, 2013). Section Cloud Computing to Facilitate Disaster Management presents a potential computing infrastructure - cloud computing, to address the demands on high-performance computing framework for processing social media data timely and effectively.

CLOUD COMPUTING TO FACILITATE DISASTER MANAGEMENT

Decision support systems for disaster management can only be best conducted when integrating a large amount of geospatial information in a collaborative environment and timely fashion. However, such systems pose several critical requirements to the underlying computing infrastructure. First, it must achieve high performance. The data, such as social media and forecasting data, to support effective decision-making during natural hazards, come in streams, and must be processed in a real-time fashion. Additionally, because most of these data are distributed across different agencies and companies and with different formats, resolutions, and semantics, it takes a relatively long time to identify, process, and seamlessly integrate these heterogeneous datasets. Second, it must be flexible. Tens to hundreds of computers are needed for the physical model simulations to run in a few hours to produce high-resolution results and support the associated decision-making process using multisourced data once such an event is detected. After the emergency, the computing resources should be released and reclaimed by other science, application, and education purpose in a few minutes without or with little human intervention. Third, it has to be resilient. In times of critical situation, system failures may occur because the adverse environmental conditions, such as physical damage, power outages, floods, etc. Hence, the big data storage, simulation, analysis, and transmission services must be able to operate during such adverse conditions (Pu and Kitsuregawa, 2013).

Most traditional computing infrastructure lacks the agility to keep up with these computing requirements by developing an elastic and resilient Cyberinfrasturcture (CI) for disaster management. Cloud computing, a new distributed computing paradigm, can quickly provision computing resource in an on-demand fashion. It has been widely utilized to address geoscience challenges of computing, data, and concurrent intensities (Yang et al., 2011). In fact, it can naturally serve as the underlying computing infrastructure of an operational system during a crisis in the following aspects:

- High performance: Cloud computing provides scientists with a complete new computing paradigm for accessing and utilizing the computing infrastructure. Cloud-computing services, especially Infrastructure as a Service (IaaS), a category of popular cloud services, can be easily adopted to offer the prevalent high-end computing technologies to provide more powerful computing capabilities. Many cloud providers offer a range of diverse computing resources for users' computing needs, such as Many Integrated Cores (MICs), Graphics Processing Units (GPUs), and Field Programmable Gate Arrays (FPGAs). For example, Amazon Elastic Compute Cloud (EC2) Cluster, with 17,024 CPU cores in total, a clock speed of 2.93 GHz per core, and 10G Ethernet network connection, was ranked as 102nd on the TOP 500 supercomputer lists in the November 2012. The high performance computing (HPC) capability of cloud computing can be easily leveraged to support critical scientific computing demands (Huang et al., 2013a).
- Flexibility: Hazard events often have annual or seasonal variability and are of short duration. Most events typically last a relatively short period from several hours (e.g., tornadoes) to several days (e.g., hurricanes). As a result, a real-time response system for such events would experience different computing and access requirements during different times of the year and even different hours within the day. During a disaster, the computing platform supporting an emergency response system should be able to automatically scale up enough computing resources to produce and deliver relevant and useful information for the end users, and to enable them to make smarter decisions, saving more lives and reducing assets loss. After the emergency response, the access to information can be reduced and the system can switch back to "normal mode" for reduced costs. Computing resources would be released for other science, application, and education purposes.

Applications, running on the cloud, can increase computing resources to handle spike workloads and accelerate geocomputation in a few seconds to minutes. Additional computing resources can be released in seconds once the workloads decrease. Previous studies (Huang et al., 2013a, 2013b, 2013c) demonstrated that cloud computing can help application-handling computing requirement spikes caused by massive data transfers, model runs, and data processing without expensive long-term investment for the underlying computing infrastructure. Therefore, an operational system based on cloud computing can respond to real-time natural hazards well.

- Resilience: Architectural resilience can be achieved in many ways including (1) having back-up redundant systems that automatically deploy when primary systems fail, or (2) employing multiple solutions to ensure that some minimum level of system functionality is available during massive system failures (Pu and Kitsuregawa, 2013). Cloud services provide an ideal platform to implement this resilient mechanism. Cloud computing providers offer computing and storage services that are globally distributed. For example, three major cloud providers, including Amazon, Microsoft, and Google, have multiple data centers around the world with the service. An image containing the configured application could be built in cloud services, and then a new replicated application can be easily launched on failover systems in a different cloud zone in a few minutes after a failure (Huang et al., 2013c).

CASE STUDIES

Through a variety of research studies and government practice, it has been widely demonstrated that online social technologies and social media like Facebook, Twitter, Google+, etc., can be employed to solve many problems during natural disasters. This section introduces several real applications to show how social media were used for emergency response and disaster coordination, and how cloud computing can facilitate these applications.

Tsunami in Japan

On March 11, 2011 at 2:46 pm local time, a massive magnitude 9.0 underwater earthquake occurred 70 km offshore of the eastern coast of Japan. The earthquake generated a tsunami that rapidly hit the eastern coast of Japan, and propagated across the Pacific Ocean to the west coast of the Americas. The tsunami wave hit the Fukushima power plant about 40 min after the earthquake, leading to the catastrophic failure of the cooling system. Several radioactive releases ensued as a result of an increase of pressure and temperature in the nuclear reactor buildings. Some releases were the result of both controlled and uncontrolled venting, whereas others were the result of the explosions that compromised the containment structures. The explosions were most likely caused by ignited hydrogen, generated by zirconium–water reaction occurring after the reactor core damage (Cervone and Franzese, 2014). The radioactive cloud was quickly transported around the world, reaching North America within a few days and Europe soon thereafter (Potiriadis et al., 2012; Vasilescu et al., 2008). Radioactive concentrations were recorded along the US West Coast within a week of the initial release (Cervone and Franzese, 2014).

Social media, including Twitter, quickly disseminated information about the developing disaster in Japan. Twitter data was harvested using a cloud computing solution deployed at Pennsylvania State University, which collected several million Tweets related to the Japanese disaster. The analysis of the Tweets was performed using Docker (https://www.docker.com/), an open-source virtualization software that allows quick distribution of data and computing on the cloud. First, a container was created to include all analysis software for filtering and plotting the Tweets. A second container with all the Tweets was created and continuously updated with additional data. The advantage of using Docker consists in the ability to allocate variable resources for the analysis of Tweets, varying from few tenths to over a 1000 cores. Furthermore, cloud-computing platform Amazon EC2 (Huang et al., 2010) is used to support Docker containers, and thus makes it possible to quickly deploy the analysis and meet the requirements of flexible resources during a crisis (section Cloud Computing to Facilitate Disaster Management).

Although the implementation of cloud-computing technology solves the problem of big data analysis, data has to be managed in a way that is suitable for distributed parallel processing. As discussed earlier, social media data such as Tweets, constantly flow in extremely large volume and with versatile contents. Recently, a NoSQL database has been popularly implemented as a better means to manage such data (Huang and Xu, 2014). This is because a NoSQL database can (1) store data that are not uniform and structured, and (2) support the utilization of multiple servers to improve the performance in a much easier way. In our system, a MongoDB, one of the popular NoSQL databases, therefore was set up to store all geolocated Tweets, plus all Tweets that made mention of several hashtags relative to the Japanese crisis.

Fig. 15.1 shows a trend of Tweets collected immediately before and after the Japan earthquake and resulting tsunami. Mentions of Japan in Tweets

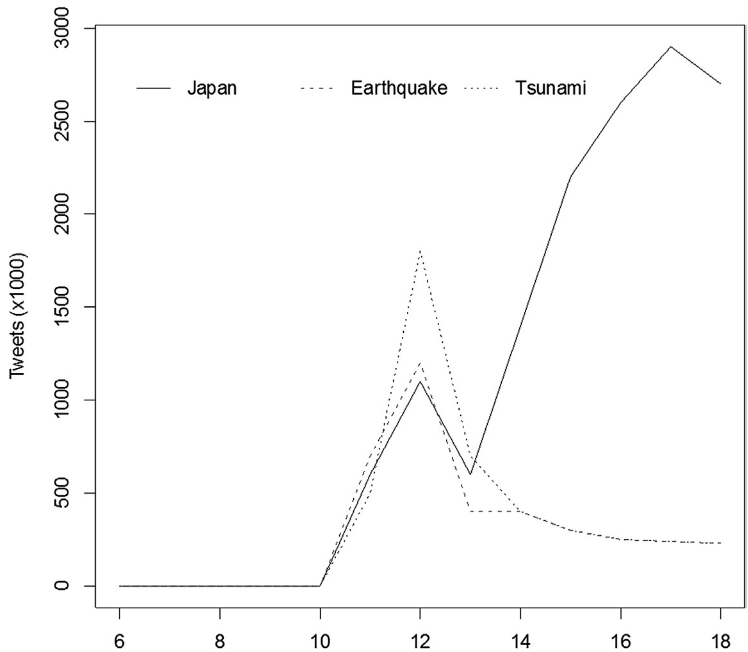

Figure 15.1 Twitter data relative to the Japanese crisis, showing the number of Tweets that include the keywords Japan, earthquake, and tsunami. In the immediate aftermath of the earthquake and resulting tsunami, Tweets including all three keywords spiked significantly, however, after March 13, the keyword Japan greatly increased as news about the crisis resonated through the social network.

peaked at nearly 3 million per day on March 16, 2011, just a few days after the event, when the widespread destruction became apparent.

Fig. 15.2 shows about 1 million geolocated Tweets collected from March 10 to March 31, 2011, within Japan. The bar graphs in the two bottom figures show the number of Tweets per longitude and latitude, to compensate for over-plotting. Taller bars indicate a higher concentration of Tweets at the corresponding longitude and latitude. The majority of the Tweets are geolocated around Tokyo and other major metropolitan areas in Japan. In the two top figures, a circle is used to indicate the 20 km restricted area around the Fukushima nuclear power plant. This exclusion zone was enacted after the nuclear leak to protect citizens from being exposed to dangerous radioactive contaminants. The data show a lack of Tweets in the exclusion zone compared to the other surrounding zones, which is to be attributed to the compliance of the residents with the mandatory evacuation order. Fig. 15.3 shows global distribution of geolocated Tweets about Japan for about 1 month after the event.

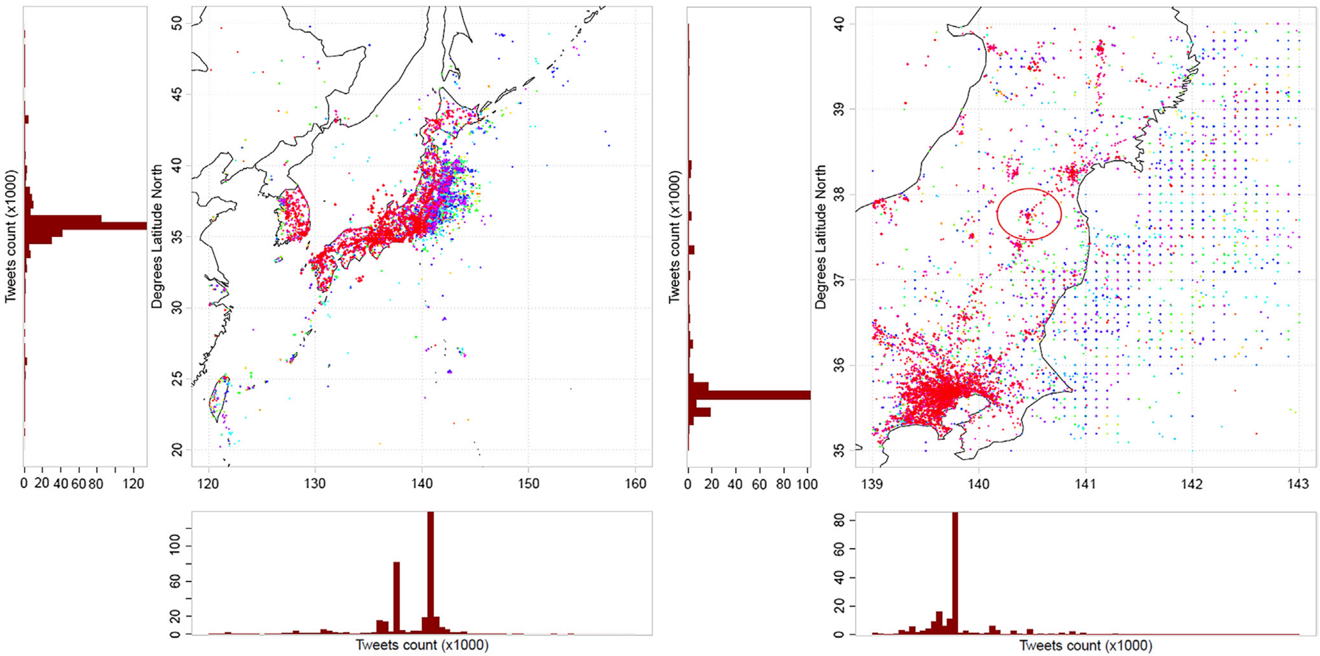

Figure 15.2 Geolocated Tweets collected from March 10 to March 30, 2011, at different scales within the Japan area. The circle shows the 20 km restricted area around the Fukushima nuclear plant. The bar graph for each axis indicates the number of Tweets along the longitude and latitude.

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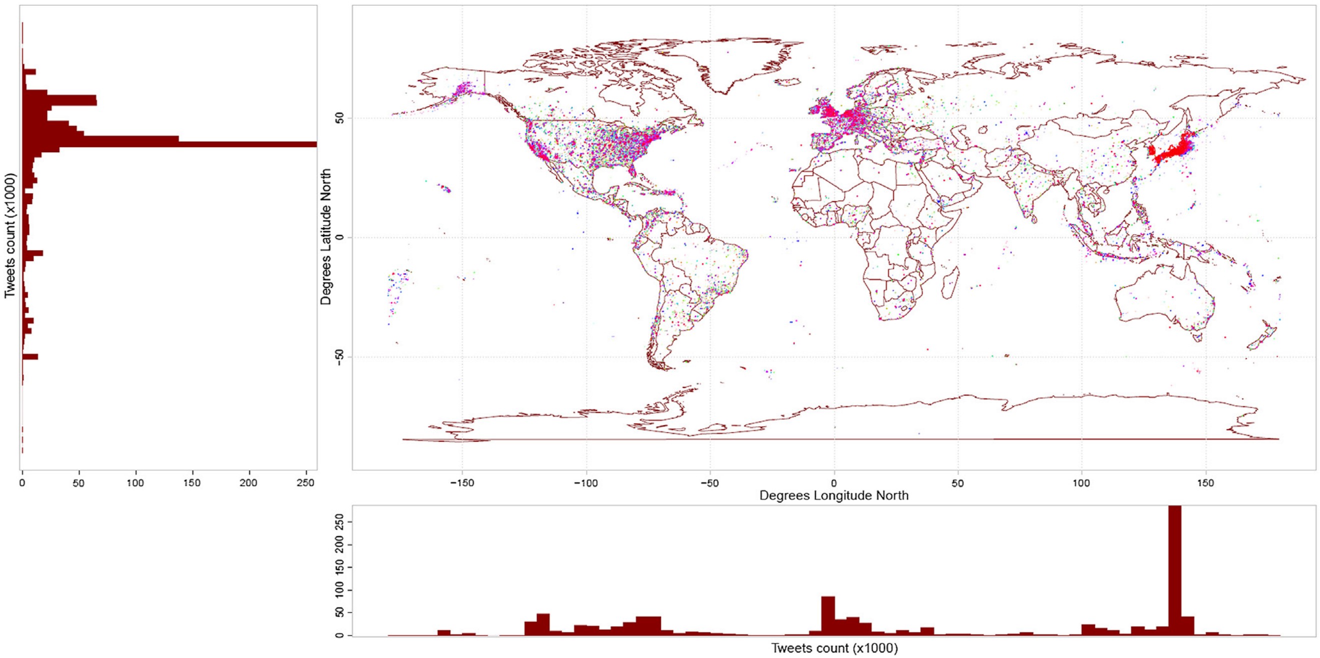

Figure 15.3 The global distribution of geolocated Tweets about Japan for about 1 month after the event.

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The analysis of Tweets shows that the social intensity worldwide increased as the radioactive cloud spread over North America and Europe. The majority of the Tweets provided alarming information about the situation in Japan, and targeted both informing about the event and soliciting help for disaster response. Furthermore, although three crisis were unfolding in parallel (tsunami inundation, earthquake damage, and radioactive release), the majority of the Tweets disproportionally discussed the radioactive release over the other two. In North America, Tweets and retweets about the Japanese crisis started immediately after the initial earthquake and the resulting tsunami. The peak of Tweets was observed on March 21, which corresponds to when sensors in Alaska and along the West coast of the United States started registering a small increase in radiation dosage. One lesson learned from the analysis of Twitter data during the Japanese disaster is the good awareness of the public to the unfolding of a major crisis.

Hurricane Sandy

Hurricane Sandy, a late-season posttropical cyclone, swept through the Caribbean and up the East Coast of the United States in late October 2012. Sandy began as a tropical wave in the Caribbean on October 19. It quickly developed, becoming a tropical depression, and then a tropical storm. On October 28, President Obama signed emergency declarations for several states expected to be impacted by Sandy, allowing them to request federal aid and make additional preparations in advance of the storm. On October 29, Sandy made landfall in the United States, striking near Atlantic City, New Jersey with winds of 80 mph. It affected 24 states in the United States, including the entire eastern seaboard from Florida to Maine and west across the Appalachian Mountains to Michigan and Wisconsin, with particularly severe damage in New Jersey and New York. Within 2 days, the region was starting to recover. As of November 1, about 4.7 million people in 15 states were without electricity, down from nearly 8.5 million a day earlier. Storm surge caused subway tunnels in Lower Manhattan to close due to flooding, but some lines were able to resume limited service. Sandy's impact was felt globally as 15,000 flights around the world were cancelled. Sandy ended up causing about $20 billion in property damage and $10 billion to $30 billion more in lost business (http://www.livescience.com/24380-hurricane-sandy-status-data.html), making it the deadliest and most destructive hurricane of the 2012 Atlantic hurricane season as well as the second-costliest hurricane in US history (http://pybossa.com/).

Based on our previous work on developing a coding schema of Tweets during Hurricane Sandy (Huang and Xiao, 2015), we developed a spatial Web portal to analyze and explore the Tweets in the different disaster phases. Several open-source software and tools were used for the prototype development. The portal supports several functions from submitting a query request to visualizing or animating the query results. Users can explore the Tweets in various themes by configuring the input parameters of the query such as temporal information (time stamps when messages were posted), area of interest (AOI, also known as spatial domain), and analytical methods (visualization or charting), etc. After obtaining query results, users are able to visualize the results to get an overall view of the spatial and temporal patterns of the Tweets related to specific topics retrieved from the database (Fig. 15.4).

The aforementioned system can support geovisualizing and analyzing disaster relevant Tweets in different themes spatially and temporally for a historical event with pre-processed data. However, exploring and visualizing massive social media for real-time events requires further development. Specifically, data from different extreme natural hazard events, especially hurricane-related ones, should be examined and integrated to develop a real-time disaster management system so that it can be applied to automatically categorize the Tweets into different themes during any new disaster of different types. Such a system could help support real-time disaster management and analysis by monitoring subsequent events while Tweets are streaming, and mining useful information. As discussed in section Cloud Computing to Facilitate Disaster Management, cloud computing can then be leveraged to process multisourced and real-time social media data. In fact, a few attempts have been made to integrate real-time social media and cloud computing to support real-time emergency response. One of the examples is Esri's severe weather map (http://www.esri.com/services/disaster-response/severe-weather/latest-news-map). It harvests multisourced data, including Twitter Tweets, YouTube videos, Flickr photos, and weather reports of various events using specific (e.g., tornado, wind storm, hail storm) from NOAA and other sources. Additionally, a cloud-based mapping platform is used to display the real-time effects of the storm via social media posts (Fig. 15.5). Although the default is to show information for "tornado," registered users can log in to track and monitor the feeds of other disaster events by searching with keywords such as "fire," "snow," etc.

Earthquake in Haiti

On Tuesday, January 12, 2010 at 4:53 pm local time, a catastrophic magnitude 7.0 earthquake occurred, with an epicenter near the town of Léogâne

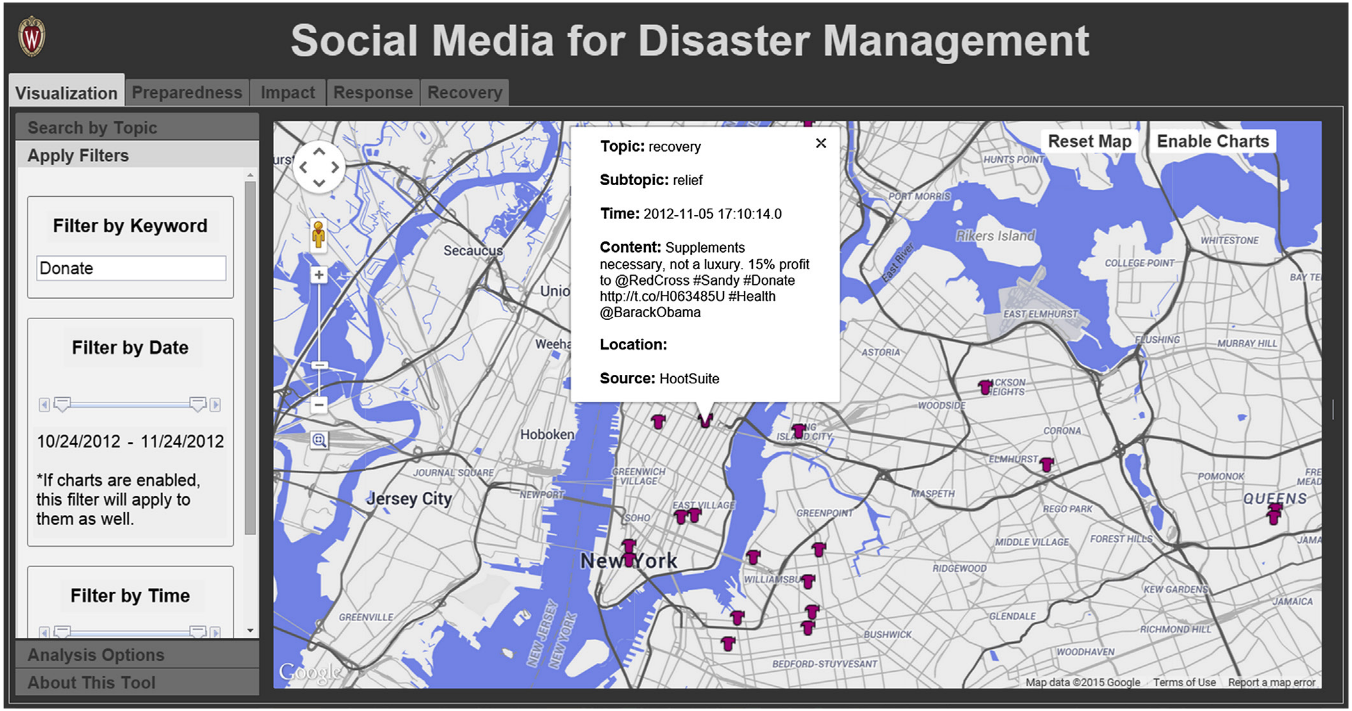

Figure 15.4 Visualizing and mining Tweets for disaster management.

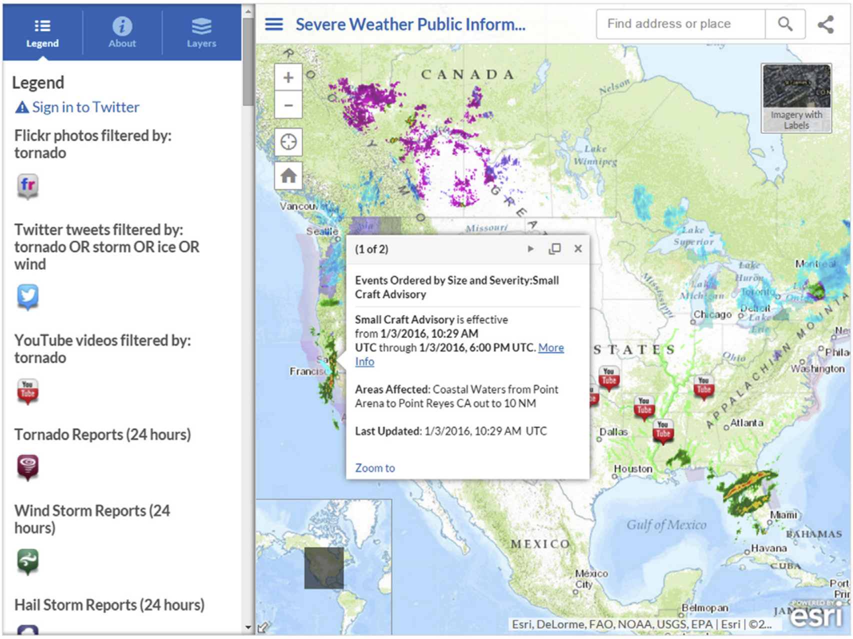

Figure 15.5 Environmental Systems Research Institute (Esri) weather map showing live storm reports, precipitation, and weather warnings along with multisourced social media content from Twitter, Flickr, and YouTube (http://www.esri.com/services/disaster-response/severe-weather/latest-news-map).

(Ouest Department), approximately 25 km (16 miles) west of Port-au-Prince, Haiti's capital (http://en.wikipedia.org/wiki/2010_Haiti_earthquake). It was the strongest quake recorded in Haiti for over 200 years. The earthquake caused devastating damage in the densely populated city of Port-au-Prince, Jacmel, and other settlements in the region. Notable landmark buildings were severely damaged or destroyed, including the Presidential Palace, the National Assembly building, the Port-au-Prince Cathedral, and the main jail. An estimated 3 million people were affected by the quake with 230,000 killed, 300,000 injured, and 1 million people left homeless (Yates and Paquette, 2011).

Many countries responded to appeals for humanitarian aid, pledging funds, and dispatching rescue and medical teams, engineers, and support personnel. Social media was successfully used as a platform to both gather and disseminate information to a global audience, and to support emergency response and disaster relief in a variety of ways.

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- Public sharing of situational information and conditions through social network sites (e.g., Twitter, Flickr, and TwitPics). The collapse of traditional media elevated social media to the principal communications tool: everyone became a journalist. As soon as the earthquake struck Port-au-Prince, the capital city of Haiti, the first pictures of the devastated scenes were posted to Twitter and Facebook and were later relayed to the world by CNN. Following that, thousands of other pictures quickly spread through TwitPics and Twitter along with well wishes (Oh et al., 2010).
- Use of wikis by both nongovernmental and government relief organization to share and collaborate via the cloud in a secure arena. For example, US government agencies employed social technologies such as wikis and collaborative workspaces as the main knowledge-sharing mechanisms (Yates and Paquette, 2011).
- Crowdsourcing and identification of individuals who could translate Creole and Haitian dialects into other languages so that first responders could identify where to target aid.
- Use of social platforms for relief efforts. Twitter users spread the way to send emergency supplies or aid money to Haiti, and shared the information on how to adopt orphaned children (Oh et al., 2010).
- Remote aid via volunteers digitizing street maps and satellite imagery and uploading these results to a shared platform. Social technologies can also be leveraged to generate geographic information which is critical for emergency management. For example, a group of OpenStreetMap users around the globe rapidly produced a detailed street map of Port-au-Prince, based on digitization of satellite imagery facilitated by social networks such as Crisis Mappers Net (Li and Goodchild, 2012), which was used by crisis responders on the ground in Haiti. Before the earthquake, the OpenStreetMap map of Port-au-Prince had very limited coverage (Fig. 15.6 left), but within only 48 h, the dataset became possibly the most complete and accurate source for that area available to first responders (Fig. 15.6 right).

CONCLUSIONS

As social media applications are widely deployed in various platforms from personal computers to mobile devices, they are becoming a natural extension to human sensory system. The synthesis of social media with human

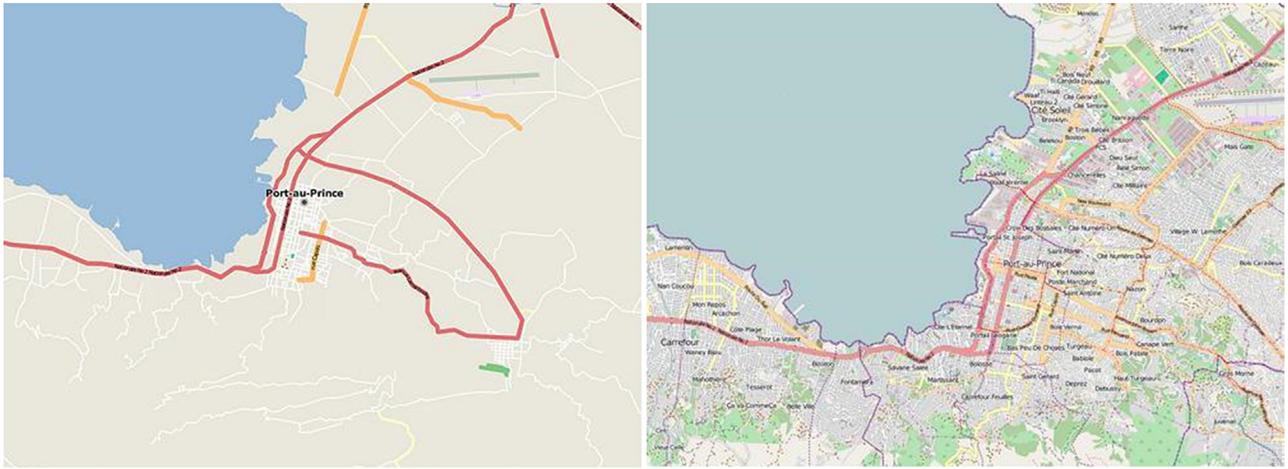

Figure 15.6 OpenStreetMap coverage before (left) and after (right) the 2010 Haiti Earthquake (http://blog.okfn.org/2010/01/15/open-street-map-community-responds-to-haiti-crisis/).

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intelligence has the potential to be the intelligent sensor network that can be used to detect, monitor, and gain situational awareness during a natural hazard with unprecedented scale and capacity. However, the rate at which these crowdsourced data are being generated exceeds our ability to organize and analyze them to extract patterns critical for addressing real-world challenges, such as effective disaster management strategies. New challenges arise from an unprecedented access to massive amounts of social media data available and accumulated every day, and on how to develop and use new tools to mine knowledge from these data streams. This chapter discusses how social media can be used to assist during various stages of disaster management, and provides a literature survey of existing relevant research. However, the great potential of using social media for disaster response comes with challenges, which are identified along with a discussion of potential solutions.

Cloud computing is a promising computing infrastructure to accelerate geoscience research and applications by pooling, elastically sharing, and integrating latest computing technologies, and deploying physically distributed computing resources (Huang et al., 2013a). As discussed in the section Case Studies, cloud computing should be integrated to design and develop an elastic and resilient CI framework for archiving, processing, mining, and visualizing social media datasets disaster management. Specifically, cloud storage may be investigated and leveraged for the massive social media data archiving for immediate disaster response use and later research studies. Elastic computing power can be leveraged to handle the computing demands from mining big social media data, and massive concurrent access of an online analytical system during emergencies. Finally, several use cases are provided to demonstrate how social media and cloud computing have been employed to study several recent disasters.

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