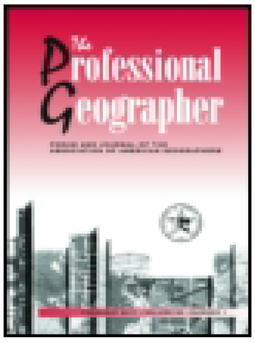

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Exploratory Spatiotemporal Analysis in Risk Communication during the MERS Outbreak in South Korea

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The 2015 Middle East respiratory syndrome (MERS) outbreak in South Korea gave rise to chaos caused by psychological anxiety, and it has been assumed that people shared rumors about hospital lists through social media. Sharing rumors is a common form of public perception and risk communication among individuals during an outbreak. Social media analysis offers an important window into the spatiotemporal patterns of public perception and risk communication about disease outbreaks. Such processes of socially mediated risk communication are a process of meme diffusion. This article aims to investigate the role of social media meme diffusion and its spatiotemporal patterns in public perception and risk communication. To do so, we applied analytical methods including the daily number of tweets for metropolitan cities and geovisualization with the weighted mean centers. The spatiotemporal patterns shown by Twitter users' interests in specific places, triggered by real space events, demonstrate the spatial interactions among places in public perception and risk communication. Public perception and risk communication about places are relevant to both social networks and spatial proximity to where Twitter users live and are interpreted in reference to both Zipf's law and Tobler's law. **Key Words: meme diffusion, MERS, social media, Twitter, Zipf's law.**

2015 年中东呼吸道症状 (MERS) 在南韩爆发后, 心理焦虑引发了混乱, 而一般假定人们透过社交媒体分享有关医院名单的传闻。分享传闻, 是传染病爆发时公共感知与风险沟通的常见形式。社交媒体分析, 提供了探问疾病爆发的公共感知与疾病沟通的时空模式一个重要窗口。此般透过社会媒介的风险沟通过程, 是模因扩散的过程。本文旨在探讨社交媒体模因扩散的角色, 及其在公共感知与风险沟通中的时空模式。为此, 我们应用包括大都会城市的每日推特数量以及具加权平均中心的地理可视化。由推特使用者对特定地方的兴趣所展现的时空模式, 并由实际的空间事件所引发, 证实了大众感知与风险沟通中, 地方之间的空间互动。地方的大众感知与风险沟通, 同时与推特使用者的社会网络和其住所的空间邻近性有关, 并根据齐普夫定律和托布勒地理学第一定律进行诠释。 **关键词: 模因扩散, MERS, 社交媒体, 推特, 齐普夫定律。**

El brote en 2015 del síndrome respiratorio del Oriente Medio (MERS), en Corea del Sur, llevó al caos causado por ansiedad psicológica, y se ha asumido que la gente compartió rumores acerca de los listados hospitalarios a través de los medios sociales. Compartir rumores es una forma común de percepción pública y comunicación de riesgo entre los individuos durante un brote. El análisis de los medios sociales ofrece una ventana importante en los patrones espaciotemporales de la percepción pública y la comunicación de riesgo acerca de brotes de enfermedad. Tales procesos de comunicación de riesgo mediados socialmente son un proceso de difusión de memes. Este artículo apunta a investigar el papel de la difusión de memes por los medios sociales y sus patrones espaciotemporales en la percepción pública y la comunicación de riesgo. Para hacerlo, aplicamos métodos analíticos, incluyendo el número diario de tuits en ciudades metropolitanas y geovisualización con los centros medios ponderados. Los patrones espaciotemporales mostrados por los intereses de usuarios de Twitter en lugares específicos, disparados por eventos en el espacio real, demuestran las interacciones espaciales entre lugares en percepción púbica y comunicación de riesgo. La percepción pública y la comunicación de riesgo acerca de lugares son relevantes para las redes sociales y para la proximidad espacial a donde viven loa usuarios de Twitter, y se interpretan con referencia tanto con la ley de Zipf como con la ley de Tobler. **Palabras clave: difusión de memes, MERS, medios sociales, Twitter, ley de Zipf.**

Since 20 May 2015 when the Centers for Disease Control and Prevention in South Korea (CDC Korea) reported the first diagnosed case of Middle East respiratory syndrome (MERS) infection, it has confirmed 186 cases, reported thirty-eight deaths, and quarantined 16,693 people to their homes (CDC Korea 2015). This epidemic event gave rise to chaos caused by psychological anxiety and resulted in considerable economic impact (Jung et al. 2016). At the beginning of the MERS outbreak, CDC Korea did not publicly release the list of places and hospitals associated with the MERS patients. Further, the mass media, including newspapers, television, and radio, could not deliver accurate information on the MERS outbreak (Yoo, Choi, and Park 2016).

New media including Internet news, social media, and text messages became "disruptive" technologies for such nondisclosure of information (Ma 2005). During the MERS outbreak in South Korea, it has been assumed that many people shared rumors about hospital lists

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relevant to the MERS cases via social media because they could not know the official hospital lists. Rumors are "unverified" statements of information spread among people (DiFonzo and Bordia 2007), which means that correct information and misinformation can coexist with rumors. The lack of reliable information can lead to the propagation of rumors (Oh, Kwon, and Rao 2010), which is prominent during moments of crisis and turmoil when uncertainties and anxieties run high (Tai and Sun 2011). The rapid growth of online social media has made it possible for rumors to spread more quickly and more broadly (Qazvinian et al. 2011).

Sharing rumors is a common form of risk communication among individuals during an outbreak (Oh, Agrawal, and Rao 2013; Maddock et al. 2015). *Risk communication* is any purposeful exchange of information between interested parties about the probabilities of adverse events (Lang, Fewtrell, and Bartram 2001). Public officials have used social media for risk communication by sending public warning messages in disasters (Sutton et al. 2014). Such communication processes are important in controlling disease outbreaks (World Health Organization [WHO] 2005). For the MERS outbreak in Korea, however, timely risk communication and transparency in outbreak information by the Korean government have not been successful (Fung et al. 2015). As such, uncontrolled risk communication about outbreak places and hospitals might have proliferated and spread among individuals based on their neighborhoods.

Research on the role of social media in disease outbreaks has expanded extensively in recent years, for illnesses such as influenza (Nagel et al. 2013; Aslam et al. 2014), bird flu (Vos and Buckner 2016), Ebola (Jin et al. 2014; Lazard et al. 2015; Odlum and Yoon 2015; Rodriguez-Morales, Castaneda-Hernandez, and McGregor 2015), dengue (Davis et al. 2011), and measles (Mollema et al. 2015; Radzikowski et al. 2016). Most studies have focused on monitoring disease outbreaks and surveillance, but they have not discussed how social media have served as risk communication to share and spread rumors about where and when outbreaks happen. As for spatial pattern analysis, Nagel et al. (2013) and Aslam et al. (2014) investigated the correlation between actual incidence and tweets about flu, influenza, whooping cough, and pertussis in different cities. Yang et al. (2016) developed a Web application for monitoring influenza outbreaks and the Ebola outbreak via social media by adding geotargeting capability for cities and regions. These studies have focused on monitoring cities and regions associated with disease outbreaks rather than spatial interactions in terms of the epidemic disease information diffusion.

In addition, prior studies have been relatively atheoretical, examining the surveillance value of tweets or the efficacy of institutional social media messages to coordinate or influence collective response to such risks. Drawing on the multilevel model of meme diffusion (M^{3}D; Spitzberg 2014), this article examines risk communication via social media. M^{3}D provides a conceptual framework that can organize many of the surveillance and intervention efforts in regard to disease outbreaks. It has sought to organize multiple levels of explanatory constructs to account for the influence of events on social media and the influence of social media on events. A meme is any message that transfers cultural information; that is, a message that can replicate information across individuals, analogous to how genes transfer information across cells. That is, memes are messages that are capable of imitation (i.e., copying) and reproduction (e.g., retweeting) and information transfer from one organism to another. Thus, all social media messages, including tweets, are memetic.

M^{3}D proposes that the diffusion duration, speed, and influence of memes are a product of variables at five levels: the meme level (e.g., tweets with fear-eliciting words might diffuse more than neutrally worded tweets), the source level (e.g., tweets from a government authority or celebrity might diffuse more than tweets from an average citizen), the social network level (e.g., tweets shared in dense social networks diffuse more rapidly within that network than in dispersed networks), the societal level (e.g., tweets that have strongly competing news events, such as Zika tweets during a political campaign, might diffuse less extensively unless they can be tied into the competing topic frames), and the geotechnical level (e.g., tweets diffuse more readily in neighboring cities).

This article postulates that information about the locations of disease outbreaks significantly influences public perception and risk communication about the disease outbreak. The objective of this article is to investigate the role of social media in public perception and risk communication with empirical studies and theoretical backgrounds about meme diffusion with the M^{3}D theoretical framework. In particular, this article aims to contribute to the theoretical framework of social media analytics from the explicit spatial interaction perspective.

Methods

The dominant social networking service in Korea is KakaoStory (46.4 percent), followed by Facebook (28.4 percent) and Twitter (12.4 percent; Kim 2015). Despite the popularity of KakaoStory, it restricts public access to user-generated contents, just like Facebook (Kakao Corp. 2016). Thus, we selected Twitter for study in this article. When CDC Korea reported the first MERS death on 1 June 2015, we started to collect the tweets with the keyword *MERS* in Korean (i.e.,). We collected tweets by Python scripts using Twitter Search application programming interfaces (APIs; Twitter 2015) and stored them in MongoDB (MongoDB 2015), an NoSQL database. We parsed the tweets with the Korean Natural Language Processing in Python toolkit (KoNLPy; Park and Cho 2014) and created subsets based on the place names mentioned in the tweets.

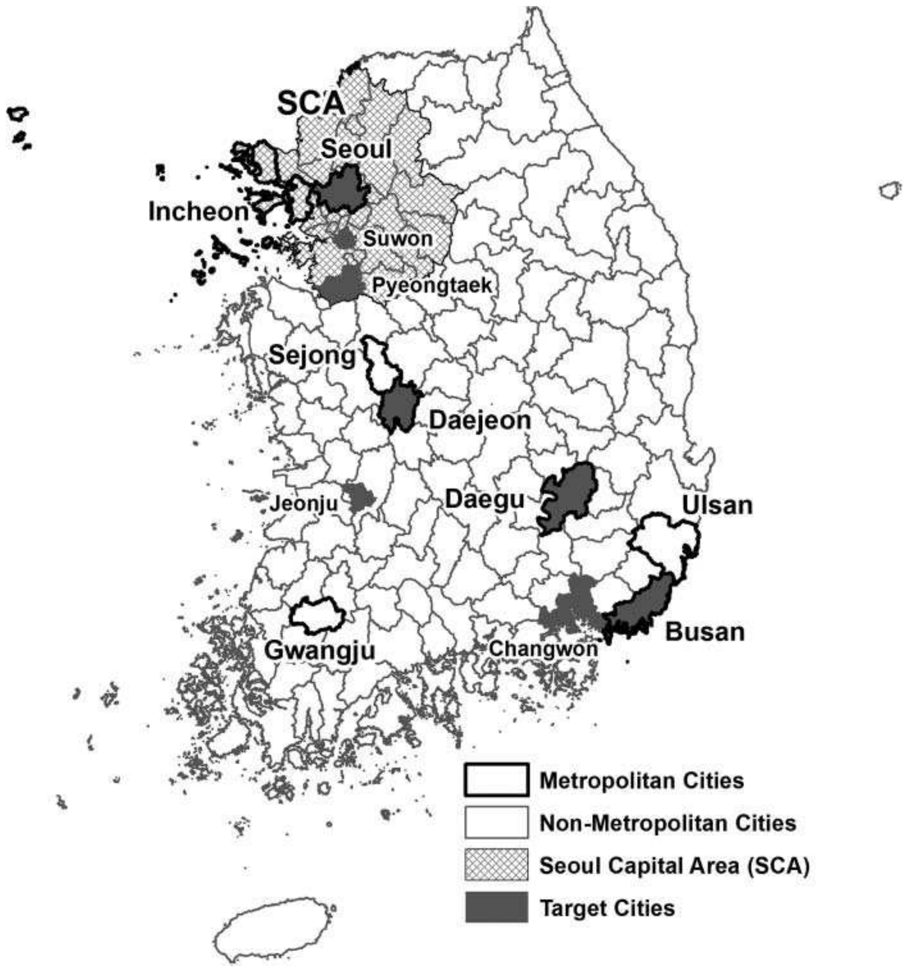

Figure 1 *Administrative divisions of Korea. The cities selected for analysis are labeled with their names.*

Data Collection and Processing

Because the Twitter Search API enabled collection of tweets published in the past seven days, the tweets published from 25 May 2015 were archived, seven days before the first reported death on 1 June, to 23 December 2015 when the Ministry of Health and Welfare declared the MERS outbreak in Korea officially over based on the WHO standards. In all, 3,771,024 tweets were collected, and 3,572,481 tweets published from 25 May to 31 July were extracted for analysis because the interest of Twitter users in the MERS outbreak waned after July. The number of Twitter users who published the tweets was 253,401.

Prior studies on spatial analysis of social media have typically analyzed tweets with geotags and user-defined locations on user profiles. Geotags are the coordinates embedded in each tweet with latitudes and longitudes, and they provide the most accurate location information for tweets. Only a small fraction of tweets (less than 1 percent) have accurate geolocation information, however (Cheng, Caverlee, and Lee 2010; Goodchild 2013). Indeed, only 2,011 (0.06 percent) tweets in this study had geotags. To cope with this issue, we analyzed the user-defined locations in user profiles. Nevertheless, some had used imaginary places or left their location empty on their profiles, resulting in invalid location information. Accordingly, we filtered out invalid location information in the user profiles with a Korea administrative divisions gazetteer.

In Korea, there are five levels of administrative divisions. We used the first and the second levels of the administrative divisions (Figure 1). The first level includes provinces, metropolitan cities, and special cities. Hereafter, metropolitan cities and special cities are referred to as metropolitan cities in this article because they belong to the first-level administrative division. The second level includes nonmetropolitan cities and counties in provinces and districts in metropolitan cities. Hereafter, cities and counties are simply referred to as nonmetropolitan cities.

To classify tweets with place names, we created a gazetteer composed of metropolitan city names in the first administrative level and nonmetropolitan city names in the second level. For the city names in the second level, we did not include the province names in the gazetteer because most Koreans did not mention them. After data processing, 788,937 tweets from 109,078 Twitter users mentioned place names. Among them, 26,543 Twitter users had valid place names in their profiles.

Temporal Analysis

We considered four temporal phases based on the levels of information uncertainty and important events: (1) before CDC Korea reported the first death (25–31 May); (2) after CDC Korea reported the first death and before the mayor of Seoul announced hospital and place names associated with a confirmed case (1–3 June); (3) after the mayor of Seoul released part of the information and before the government released all the information (4–6 June); and (4) after the government released all the information (7 June–31 July). The first step involved plotting the daily numbers of all tweets, retweets, nonretweets, and unique users to illustrate their temporal changes and examine the relationships between the number of users and the number of tweets. Next, the daily numbers of tweets for all eight metropolitan cities (Figure 1) were plotted to investigate whether these cities had distinctive patterns of temporal change. Analysis focused on the metropolitan cities because they were highly populated areas where the majority of the Twitter users distributed, thereby ensuring the quantity of tweets for analysis. Finally, the top ten words of the highest frequencies mentioned in tweets by different time periods were extracted to investigate whether the words of interests changed over time.

Spatial Analysis

To examine the spatial interactions between user locations and place names mentioned in their tweets, four metropolitan cities (i.e., Seoul, Daejeon, Daegu, and Busan) and four nonmetropolitan cities (i.e., Pyeongtaek, Suwon, Jeonju, and Changwon) were selected that are spatially dispersed within South Korea (Figure 1). For metropolitan cities, Seoul and Busan are the first and the second most populated cities located, respectively, at the northwest and the southeast of Korea, between which Daejeon and Daegu are located. For nonmetropolitan cities, Pyeongtaek and Suwon are located near Seoul and within the Seoul Capital Area (SCA), and they are relevant to the first confirmed case. Conversely, Jeonju and Changwon are the most populated cities in the southwest and the southeast of Korea, respectively, other than metropolitan cities. These eight selected cities are referred to as “target cities” in this article for spatial analysis.

The distributions of Twitter users who mentioned each target city were plotted, as well as the distributions of the city names mentioned by Twitter users who lived in each target city. Next, to explore spatial patterns, the weighted mean center was calculated (Mitchell 2005):

$$\overline{X} = \frac{\sum_{i=1}^{n} \omega_i x_i}{\sum_{i=1}^{n} \omega_i} \quad \overline{Y} = \frac{\sum_{i=1}^{n} \omega_i y_i}{\sum_{i=1}^{n} \omega_i}, \tag{1}$$

where n denotes the total number of cities, x and y are the coordinates of the centroids of the city boundaries,

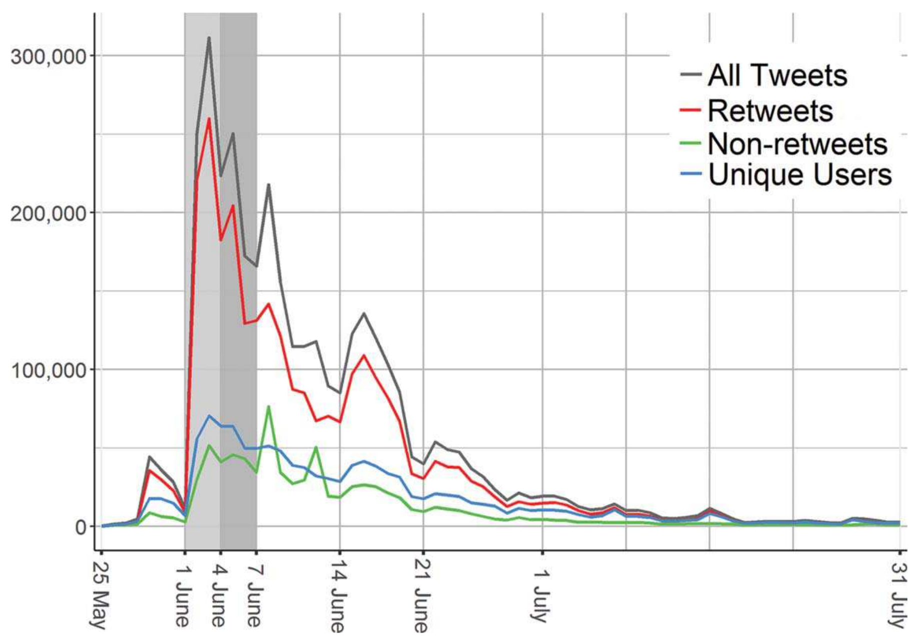

Figure 2 *The daily number of tweets and the unique users. The light gray and the dark gray shades represent the second and the third phases, respectively. (Color figure available online.)*

Table 1 *The top ten words in tweets during different time periods from May to July 2015*

First phase	Second phase	Third phase		Fourth phase		
25–31 May	**1–3 June**	**4–6 June**	**7–13 June**	**14–20 June**	**21–30 June**	**July**
Patient	Patient	Hospital	Hospital	Patient	Hospital	Hospital
Infection	Hospital	Patient	Patient	Hospital	Patient	Government
Fatal	Infection	Government	Government	Infection	Government	National Intelligence Service
Government	Government	Wonsoon Park	Infection	Government	President	Seworl-ho
Disease	Korea	Infection	Seoul	Samsung	People	People
Hospital	Camel	Seoul	Samsung	People	Samsung	President
Quarantine	Quarantine	Medical doctor	Confirmed	President	Guenhye Park	Patient
Suspected	Mask	Confirmed	Wonsoon Park	Human	Situation	Situation
China	Human	Quarantine	Human	Guenhye Park	Medical	Guenhye Park
Anthrax	People	Human	Quarantine	Wonsoon Park	Seworl-ho	Samsung

Note: For the fourth phase, June was divided on a weekly basis, but July was not because of its relatively small number of tweets. The words are listed in descending order of their frequencies mentioned in tweets. Wonsoon Park is the Mayor of Seoul, Guenhye Park is the President, and Samsung is probably related to Samsung Hospital.

and ω is the weight assigned by the number of population or the number of Twitter users in each city. Then, the locations of the weighted mean centers were selected by the number of Twitter users in relation to the weighted mean center of population. Finally, the relationship between the number of Twitter users and the population of the cities was tested with Pearson's correlation coefficient to examine if the patterns of Twitter user numbers followed the population sizes of cities.

Results and Discussion

Overall Temporal Patterns

Temporal analysis of the daily number of all tweets showed three noticeable peaks (Figure 2), reflecting that real space events could evoke social media traffic. After CDC Korea reported the first MERS death on 1 June 2015, the daily number of tweets drastically increased and peaked on 3 June, marking the first and the highest peak. The second peak date was 5 June, one day after the mayor of Seoul, Wonsoon Park, announced hospital and place names about a MERS case in Seoul. After the announcement, the mayor's name was in the top ten words contained in tweets (Table 1). The third peak date was 8 June, one day after the government released detailed information about the MERS outbreak. The daily number of tweets about MERS then gradually declined. The three peak dates corresponded well to the four phases defined in the method section. The temporal pattern of retweets was similar to that of all tweets, and the highest peak date of the number of nonretweets was 8 June 2015 (Figure 2) when the government released the detailed information about the MERS outbreak, including hospital and place names where the confirmed patients visited.

Analysis of the top ten words in the tweets during different time periods showed that *hospital* was ranked the sixth in late May but became the second and the first frequently mentioned word in early June. It was evident that the first MERS death on 1 June triggered the explosion of interest in the MERS outbreak. The top ten words in the third phase also included a place name (i.e., Seoul) and the mayor's name, possibly related to the announcement by the mayor of Seoul or the MERS confirmed case in Seoul. Hospital remained the top mentioned word in tweets in the first week of the fourth phase (7–13 June), and *Samsung* emerged among the top ten words (Table 1). This might be due to the information released by the government about the hospital and place names where the confirmed patients visited, including Samsung Hospital. Then, the mayor of Seoul's name and the president's name were among the top ten words in different weeks of June (Table 1), implying some possible political debates in tweets.

Investigation of the relationship between the number of users and the number of tweets showed that few people published many tweets, and most Twitter users retweeted once or twice during the conversation and debates. For instance, the top ranked user published 5,402 tweets, and 171 users published more than 1,000 tweets (Figure 3). Some of the heavy Twitter users were media companies, but there were also many nonmedia user accounts.

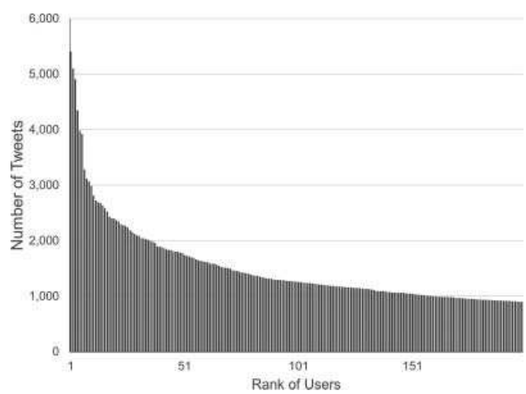

Figure 3 *The relationship between users and the number of their tweets. The users are ranked by their total number of tweets and the top 200 users are shown.*

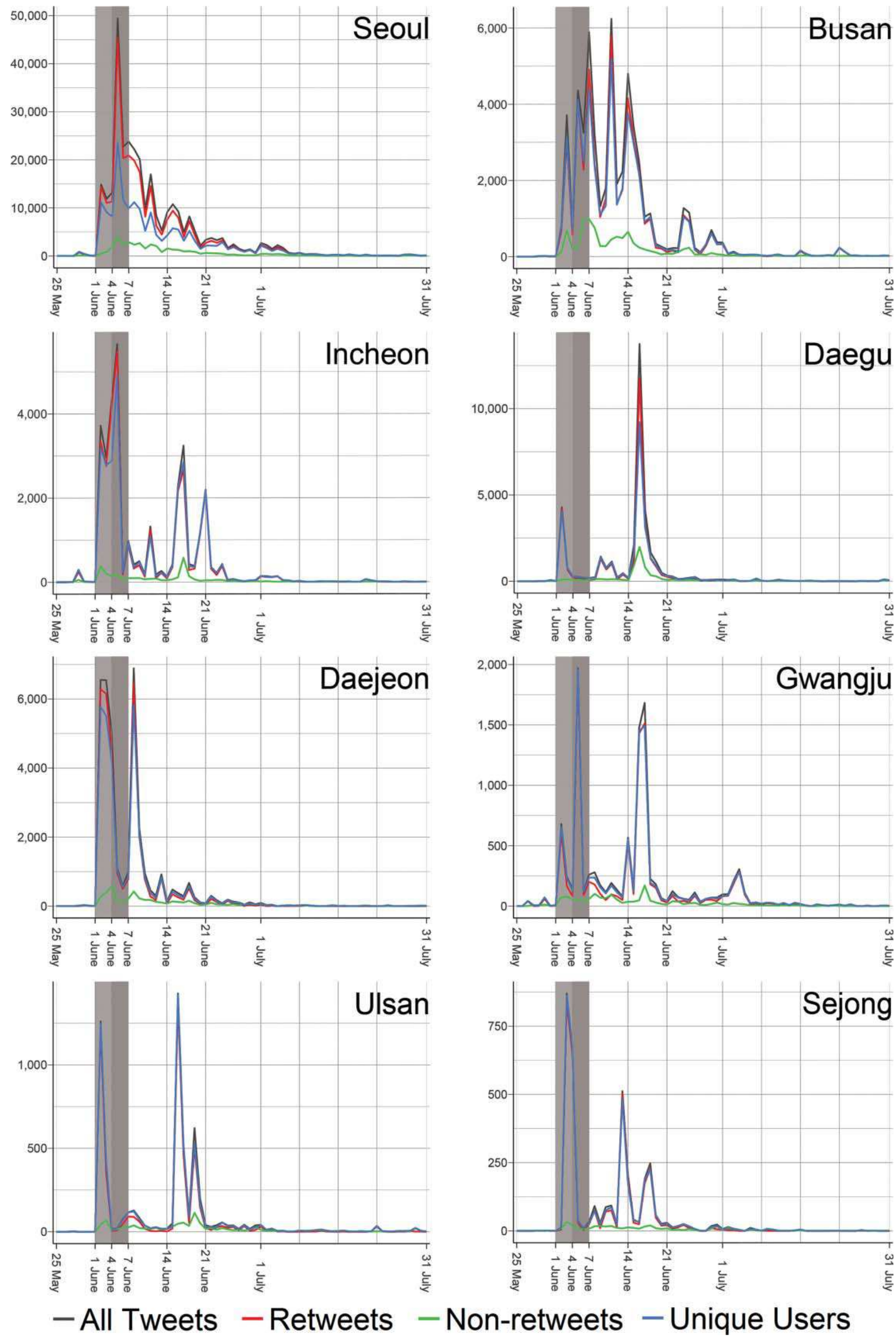

Figure 4 *The daily number of tweets and unique users for metropolitan cities. The cities are arranged by population size. (Color figure available online.)*

Temporal Patterns in Metropolitan Cities

Comparison of temporal change in the daily numbers of tweets for the eight metropolitan cities reveals distinctive patterns for individual cities (Figure 4). In the analysis of all tweets (Figure 2), the first peak date is in the second phase (1–3 June), whereas the peak dates of the tweets for Seoul, Incheon, and Gwangju are in the third phase (4–6 June; Figure 4). The peak dates for Busan, Ulsan, and Daegu are much later in mid-June (i.e., the fourth phase).

Although Seoul and Incheon are spatially adjacent, their temporal patterns are different. The daily number of

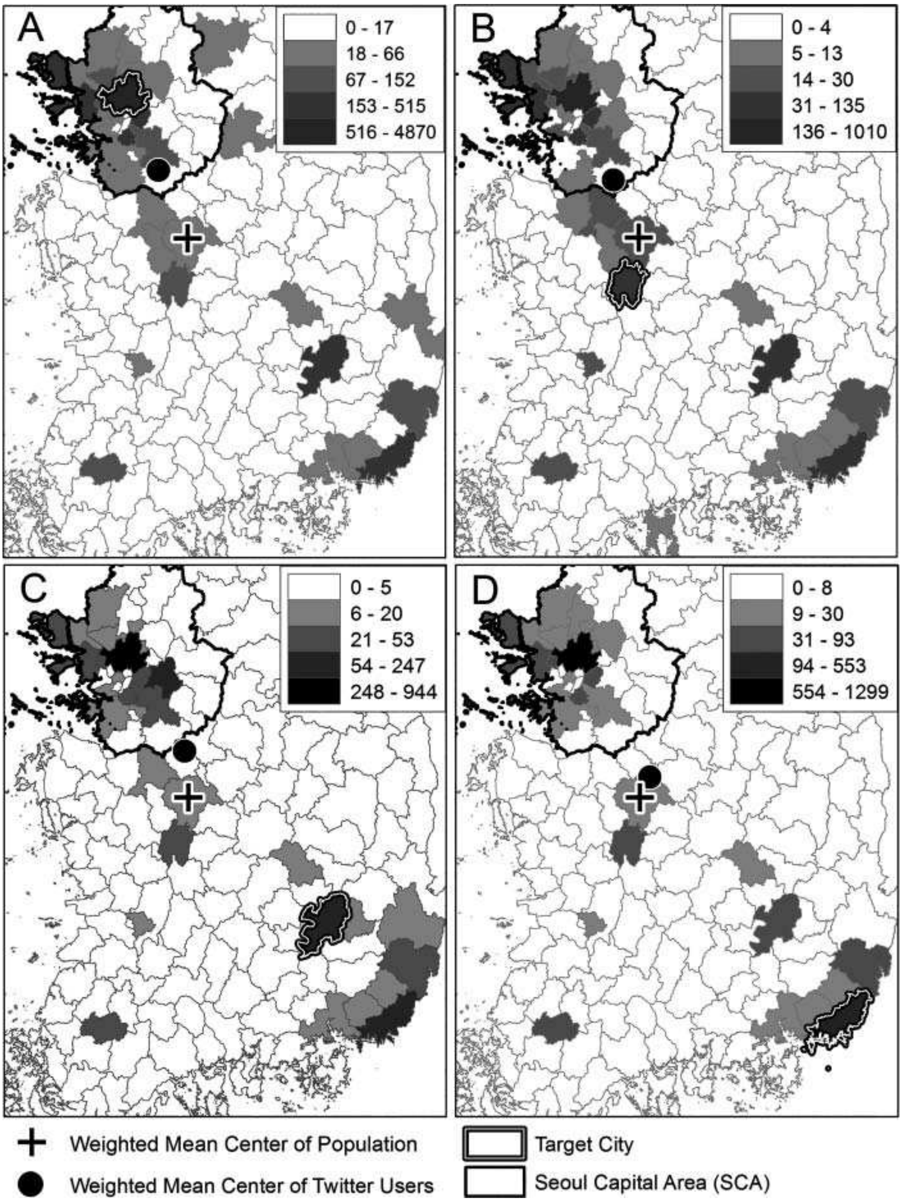

Figure 5 *Spatial distribution of Twitter users who mentioned the target metropolitan city of (A) Seoul, (B) Daejeon, (C) Daegu, and (D) Busan. Darker grays indicate higher numbers of Twitter users.*

tweets for Seoul exhibits a gradual declining trend after the first peak date on 5 June 2015, but for Incheon, there are two more high peaks in mid-June. For Daejeon, the highest peak of tweets is on 8 June 2015, one day after the government released the information about the MERS outbreak. The temporal pattern of tweets in Busan is very dynamic, with several high numbers of daily tweets for the first half of June; its highest peak is on 11 June when the mass media reported on the first MERS case in Busan. Conversely, Daegu shows a very unique pattern. Its daily number of tweets peaked when the mass media released the first confirmed case in Daegu, but the rest of the time periods observed distinctively lower number of tweets than the peak.

Spatial Patterns and Interactions

Analysis of the locations defined in the user profiles provides insights into the spatial distribution of the Twitter users and their risk communication about the MERS outbreak. Figures 5 and 6 show the spatial distributions of the Twitter users who mentioned the target cities. Each black dot on the maps indicates the mean center weighted by the number of Twitter users

Table 2 *The top ten cities of Twitter users who mentioned each of the eight target cities*

Target cities	Total number of Twitter users	1	2	3	4	5	6	7	8	9	10	Rank
Seoul	8,503	Seoul (4,870)	Busan (515)	Incheon (287)	Seongnam (241)	Daegu (233)	Suwon (220)	Daejeon (152)	Gwangju (140)	Bucheon (138)	Ulsan (111)	1
Daejeon	1,986	Seoul (1,010)	Busan (135)	Daejeon (124)	Incheon (66)	Daegu (58)	Suwon (55)	Seongnam (53)	Gwangju (30)	Ulsan (25)	Yongin (23)	3
Daegu	2,074	Seoul (944)	Daegu (247)	Gwangju (177)	Busan (139)	Incheon (53)	Seongnam (47)	Suwon (42)	Daejeon (29)	Ulsan (26)	Yongin (24)	2
Busan	2,845	Seoul (1,299)	Busan (553)	Daegu (93)	Incheon (81)	Bucheon (80)	Seongnam (57)	Suwon (52)	Ulsan (51)	Gwangju (44)	Daejeon (41)	2
Pyeongtaek	3,005	Seoul (1,606)	Busan (180)	Incheon (112)	Suwon (95)	Daegu (89)	Seongnam (71)	Daejeon (57)	Gwangju (55)	Bucheon (44)	Pyeongtaek (42)	10
Suwon	1,575	Seoul (666)	Suwon (220)	Busan (92)	Bucheon (71)	Seongnam (58)	Incheon (47)	Daegu (44)	Yongin (26)	Daejeon (23)	Gwangju (20)	2
Jeonju	439	Seoul (224)	Jeonju (24)	Busan (23)	Gwangju (16)	Seongnam (15)	Incheon (15)	Daegu (14)	Suwon (11)	Yongin (9)	Bucheon (5)	2
Chang-won	293	Seoul (116)	Changwon (51)	Busan (30)	Daegu (9)	Gimhae (7)	Yongin (6)	Seongnam (5)	Ulsan (5)	Incheon (4)	Daejeon (4)	2

Note: The values in the brackets denote the number of Twitter users. The rank column indicates the rank of the target city among the top ten cities of Twitter users.

who mentioned the specific target city. For metropolitan target cities, all dots are above the cross mark, which is the mean center weighted by all city populations and close to the SCA (Figure 5). Such a consistent pattern is likely relevant to the spatial pattern of the population in Korea.

The population sizes of Korean cities follow the rank size rule of cities (i.e., Zipf's law; Organization for Economic Cooperation and Development 2012). The most populated city, Seoul, is approximately 10 million in population; the second largest city, Busan, is 3.4 million in population. In addition, Seoul is surrounded by a number of cities, each of which has approximately 1 million in population. Because half of the population of Korea lives in the SCA, more Twitter users and more tweets published from the SCA are expected. The Pearson correlation confirms the strong relationship between the number of Twitter users and the population of cities ($r = 0.93$, $p = 0.000$), indicating that the number of Twitter users follows Zipf's law based on population size. The pattern of Zipf's law is also noticeable from the number of Twitter users (Table 2). For example, the majority of the users who mentioned Seoul are from Seoul (4,870), about ten times more than Busan (515). Similarly, for Daejeon, Pyeongtaek, and Jeonju, Seoul has the highest number of Twitter users who mentioned these target cities, and its numbers of Twitter users are almost nine or ten times more than the second ranked city (Table 2).

Migration in Korea can explain why people in Seoul have interests in other cities. Many young people have migrated from nonmetropolitan cities to metropolitan cities and the SCA. Their tweets might therefore reflect the concerns of their family and friends in their home cities. Consequently, the weighted mean centers of Twitter users who mentioned the four metropolitan target cities are close to the SCA (Figure 5). The locations of the black dots, however, move southeastward from Figure 5A to Figure 5D, corresponding to the locations of the target cities. The dot for Daejeon (Figure 5B) is slightly lower than that for Seoul (Figure 5A). The dot for Daegu (Figure 5C) is lower than that for Daejeon (Figure 5B) because Daegu is southeast of Daejeon. The location of the dot for Busan almost overlaps with the cross mark (Figure 5D).

Conversely, for the nonmetropolitan target cities, the dots of Pyeongtaek (Figure 6A), Suwon (Figure 6B), and Jeonju (Figure 6C) are at a similar location within the SCA. That is because individuals in the SCA, particularly from Seoul, published most of the tweets referring to these cities (Table 2). For example, the number of Twitter users who mentioned Jeonju is 439, of whom 224 (51 percent) users are from Seoul and 24 (5 percent) are from Jeonju. Thus, the location of the black dot (Figure 6C) is closer to the SCA than to Jeonju. On the other hand, Changwon exhibits a different spatial pattern. The total number of Twitter users who mentioned Changwon is 293, of whom 116 (40 percent) live in Seoul and 51 (17 percent) in Changwon (Table 2). Consequently, the location of the dot for Changwon is farther away from the SCA than that for Jeonju. The different location of the weighted mean center of Twitter users for Changwon might imply the increase of public perception and risk communication between individuals who live in Changwon.

Figures 7 and 8 show the spatial patterns of cities mentioned by Twitter users who lived in each of the target cities. The patterns suggest that Twitter users in the target cities not only have interests in their cities but also in other cities, because the higher numbers of Twitter users are not just found in the target cities where the users live. For the metropolitan target cities, the locations of the black dots correspond to those of the metropolitan cities. Daegu (Figure 7C) is opposite

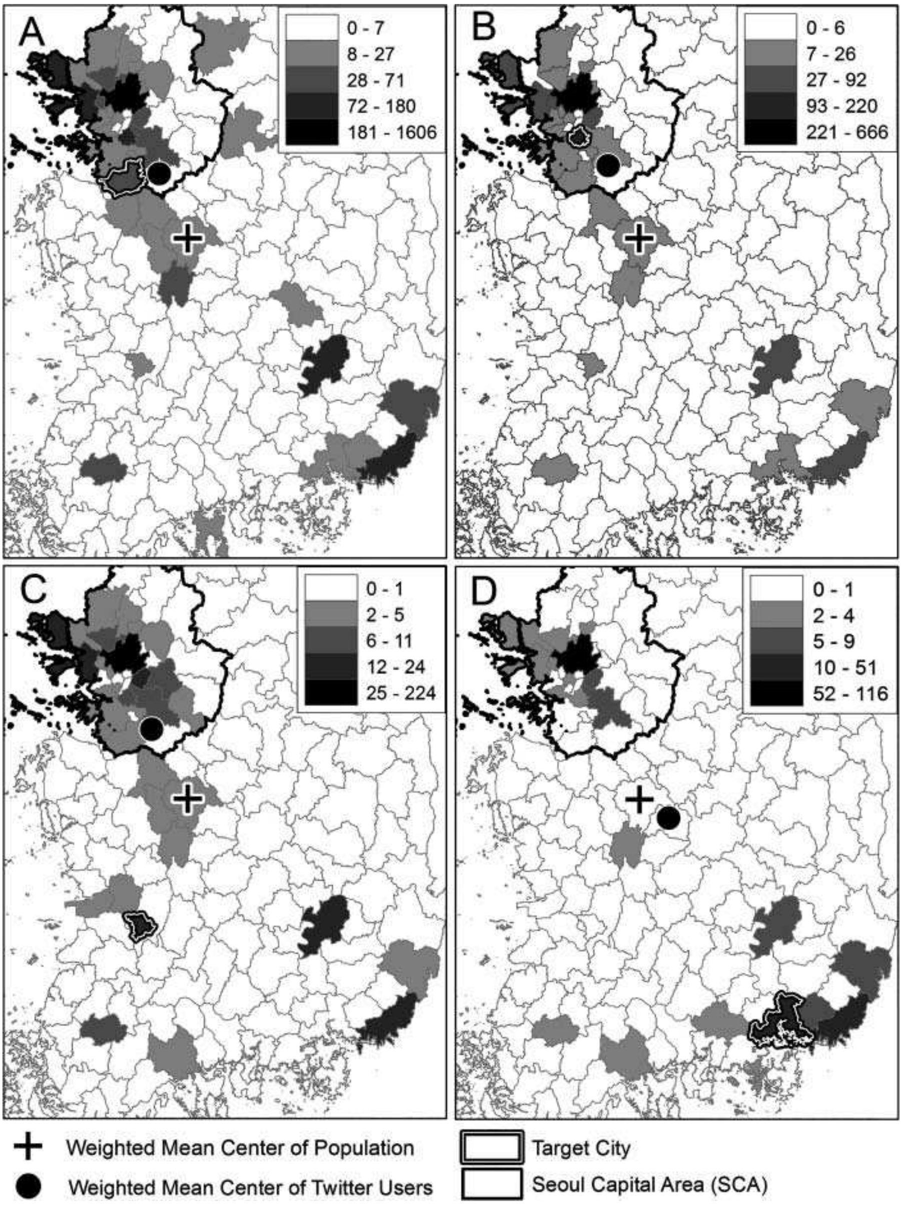

Figure 6 *Spatial distribution of Twitter users who mentioned the target nonmetropolitan city of (A) Pyeongtaek, (B) Suwon, (C) Jeonju, and (D) Changwon. Darker grays indicate higher numbers of Twitter users.*

to Seoul (Figure 7A), and the locations of their dots are opposite from the weighted mean center of population, indicated by the cross mark. Busan (Figure 7D) is to the southeast of Daegu (Figure 7C), and the dot of Busan is also to the southeast of Daegu. Likewise, for the nonmetropolitan target cities, the dot for Jeonju, a city in southwestern Korea, is to the southwest of the cross mark (Figure 8C). In contrast, Changwon is in southeastern Korea, and the dot is also to the southeast of the cross mark (Figure 8D). Comparison of these weighted mean centers illustrates that public perception and risk communication are relevant to where individuals live.

The list of the top ten city names mentioned by users from the target cities shows that the target cities are ranked either the first or the second (Table 3). The rank of Seoul is second when the rank of the target cities is the first. The difference in the number of Twitter users between the first ranked and the second ranked cities is, however, small, suggesting a lesser influence by the underlying population size (Zipf's law) but the possibility of the influence by spatial proximity (Tobler's law). Nevertheless, the first ranked cities have two or three times more Twitter users than the third ranked cities, which is close to Zipf's law.

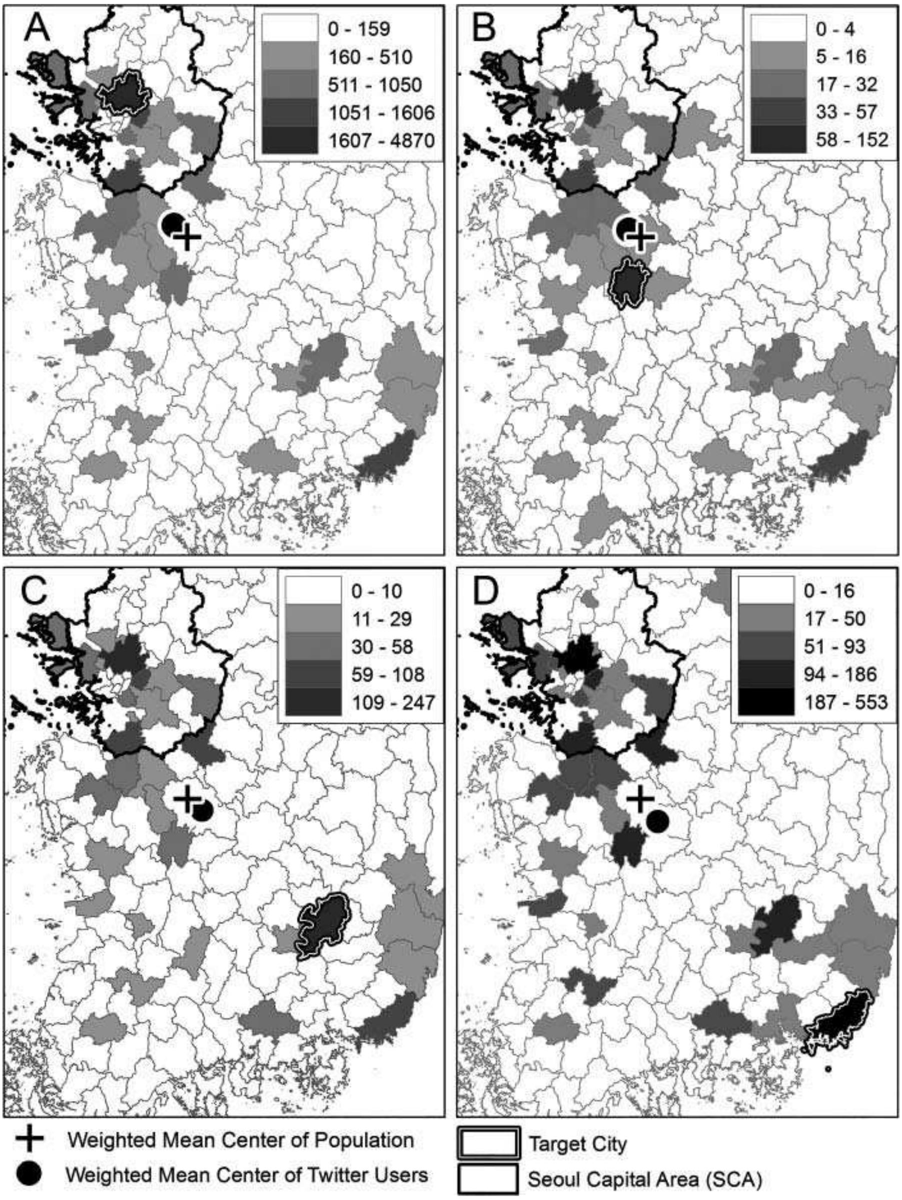

Figure 7 *Spatial patterns of cities mentioned by Twitter users from the target metropolitan city of (A) Seoul, (B) Daejeon, (C) Daegu, and (D) Busan. Darker grays indicate more target city users who have interests in those cities.*

Linking Spatial Patterns to the M^3D Framework

The spatial patterns of Twitter users demonstrate the spatial interactions between cities in public perception and risk communication. Twitter users show their perception in not only their cities but also other cities far from them (e.g., users in Busan mention Seoul). The particular patterns of meme generation in such instances can serve as a social signaling process expressing concerns both about place and as indicative of place of origin. M^3D explains that such collective behavior is both a cause and a reaction to multiple levels of social media activity: meme, source, social network, societal, and geotechnical. The highest peak date of all tweets triggered by the first death is relevant to the meme influences. The highest peak date of nonretweets involves the government announcement and illustrates the source influences. The pattern in which most of the weighted mean centers of Twitter users are close to the SCA appears to be caused by social network influences. Political debates in tweets reflect societal influences. The comparison of the weighted mean centers between Twitter users and population shows proximity-based geotechnical influences on risk communication between individuals.

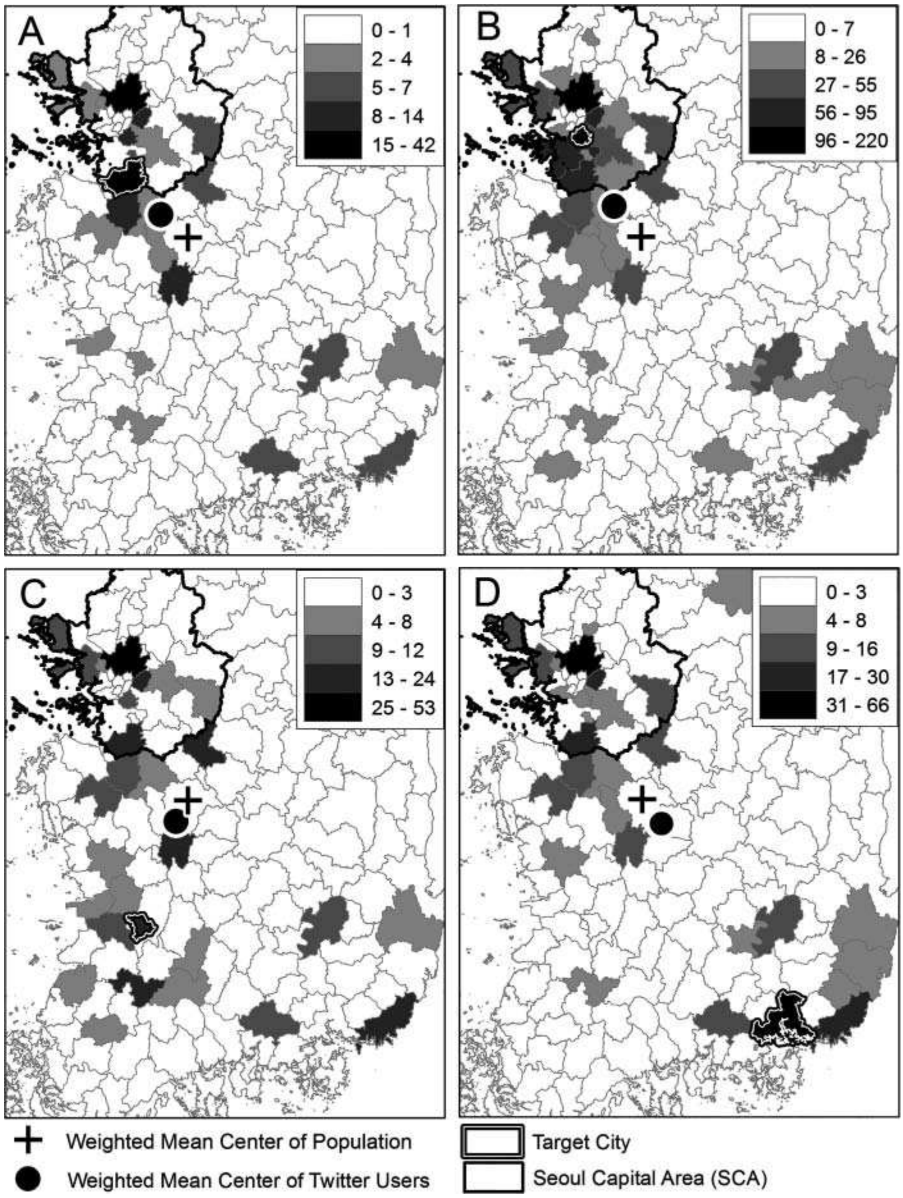

Figure 8 *Spatial patterns of cities mentioned by Twitter users from the target nonmetropolitan city of (A) Pyeongtaek, (B) Suwon, (C) Jeonju, and (D) Changwon. Darker grays indicate more target city users who have interests in those cities.*

Our results suggest that all of the levels of M^3D are not isolated but affect each other. In the spatial perspective, we highlight two levels, social network and geotechnical influences. To date, spatial analysis and social network analysis have separately contributed to human dynamics research, but there are strong conceptual overlaps of the two approaches (Shaw, Tsou, and Ye 2016). Luo and MacEachren (2014) understand such overlaps as the extension of Tobler's First Law of Geography in terms of social network distance, which reflects "implicit" spatial patterns. In our results, we also observe the overlaps of social network and geotechnical influences. Our understanding for social network, however, is based on Zipf's law, which reflects "explicit" spatial patterns.

People might publish tweets about other cities far from their cities because they are worried about family and friends in other cities, which involves their social network distance. Indeed, Scellato et al. (2011) argued that social ties are not influenced by only geographic factors. On the other hand, they might have simply wanted to propagate information about the MERS outbreak. Because they spread information to unspecified individuals, such activities relate not only to social network distance but to meme sources and societal influences. The spread of tweets referring to Seoul is likely relevant

Table 3 *The top ten cities mentioned by Twitter users who live in each of the eight target cities*

Target cities	**Total number of Twitter users**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Rank**
Seoul	27,675	Seoul (4,870)	Pyeongtaek (1,606)	Seongnam (1,598)	Busan (1,299)	Daejeon (1,010)	Daegu (944)	Incheon (915)	Suwon (666)	Gunsan (559)	Bucheon (510)	1
Daejeon	979	Seoul (152)	Daejeon (124)	Pyeongtaek (57)	Seongnam (54)	Busan (41)	Daegu (29)	Incheon (25)	Gunsan (20)	Cheonan (19)	Jinju (16)	2
Daegu	1,858	Daegu (247)	Seoul (233)	Seongnam (108)	Busan (93)	Pyeongtaek (89)	Daejeon (58)	Incheon (51)	Suwon (44)	Jinju (36)	Gunsan (29)	1
Busan	3,749	Busan (553)	Seoul (515)	Seongnam (186)	Pyeongtaek (180)	Daegu (139)	Daejeon (135)	Suwon (92)	Incheon (89)	Jinju (67)	Bucheon (65)	1
Pyeongtaek	152	Pyeongtaek (42)	Seoul (26)	Seongnam (14)	Daejeon (10)	Suwon (10)	Jinju (7)	Osan (7)	Busan (5)	Daegu (5)	Incheon (4)	1
Suwon	1,611	Suwon (220)	Seoul (220)	Pyeongtaek (95)	Hwaseong (83)	Seongnam (69)	Daejeon (55)	Busan (52)	Incheon (44)	Daegu (42)	Yongin (35)	1
Jeonju	449	Seoul (53)	Jeonju (24)	Daejeon (22)	Sunchang (21)	Seongnam (20)	Busan (19)	Pyeongtaek (18)	Incheon (12)	Gimje (12)	Suwon (11)	2
Chang-won	496	Seoul (66)	Chang-won (51)	Busan (30)	Pyeongtaek (27)	Seongnam (22)	Daejeon (13)	Daegu (13)	Incheon (12)	Jinju (12)	Sunchang (8)	2

Note: The values in the brackets denote the number of Twitter users. The rank column represents the rank of the target city among the top ten cities listed.

to the MERS cases in Seoul or the political debates about the mayor of Seoul. Due to multiple purposes, only some tweets might be directly relevant to personally relevant risk communication. Accordingly, social network influences of M^3D can involve explicit spatial patterns based on Zipf's law rather than implicit spatial patterns based on Tobler's law. For geotechnical influences, the comparison of the weighted mean centers illustrates that the spatial patterns of risk communication do not follow solely Zipf's law, and the explicit Tobler's law is still valid. The first or the second ranked cities in the number of Twitter users are relevant to users' cities (Table 2 and Table 3), which reflects the geotechnical influences envisioned by M^3D.

Conclusions

This article has found through the spatial analysis of the weighted mean centers of Twitter users and population that the spatial patterns of risk communication are a combination of Zipf's law and Tobler's law. Particularly, Zipf's law helps explain the risk communication and the public perception in terms of the social network influences as an "explicit" spatial concept. In addition, this article has illustrated how each level of the M^3D is relevant to understanding the role of social media (i.e., Twitter) for serving as a social signal of response to a potential epidemic. The results of this article also suggest the different roles of certain meme sources, which in this case reflect the central government and local governments. Because people tend to have interests in other cities as well as their cities, the central government should play a role in collecting and disseminating overall information about the outbreak. Risk communication via social media has become important, and the rapid response of governments through social media has become feasible. Thus, because the local governments can investigate, monitor, and share more detailed local information about their places, we need to encourage risk communication by local governments through social media. The role of the local governments is thus more important because the information provided by the local governments can reduce the uncertainty of information about the outbreak and cope with misinformation associated with their cities. ■

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