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Use of Twitter social media activity as a proxy for human mobility to predict the spatiotemporal spread of COVID-19 at global scale

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Abstract

As of February 27, 2020, 82,294 confirmed cases of coronavirus disease (COVID-19) have been reported since December 2019, including 2,804 deaths, with cases reported throughout China, as well as in 45 international locations outside of mainland China. We predict the spatiotemporal spread of reported COVID-19 cases at the global level during the first few weeks of the current outbreak by analyzing openly available geolocated Twitter social media data. Human mobility patterns were estimated by analyzing geolocated 2013–2015 Twitter data from users who had: i) tweeted at least twice on consecutive days from Wuhan, China, between November 1, 2013, and January 28, 2014, and November 1, 2014, and January 28, 2015; and ii) left Wuhan following their second tweet during the time period under investigation. Publicly available COVID-19 case data were used to investigate the correlation among cases reported during the current outbreak, locations visited by the study cohort of Twitter users, and airports with scheduled flights from Wuhan. Infectious Disease Vulnerability Index (IDVI) data were obtained to identify the capacity of countries receiving travellers from Wuhan to respond to COVID-19.

Our study cohort comprised 161 users. Of these users, 133 (82.6%) posted tweets from 157 Chinese cities (1,344 tweets) during the 30 days after leaving Wuhan following their second tweet, with a median of 2 (IQR= 1–3) locations visited and a mean distance of 601 km (IQR= 295.2–834.7 km) traveled. Of our user cohort, 60 (37.2%) traveled abroad to 119 locations in 28 countries. Of the 82 COVID-19 cases reported outside China as of January 30, 2020, 54 cases had known geolocation coordinates and 74.1% (40 cases) were reported less than 15 km (median = 7.4 km, IQR= 2.9–285.5 km) from a location visited by at least one of our study cohort's users. Countries visited by the cohort's users and which have cases reported by January 30, 2020, had a median IDVI equal to 0.74. We show that social media data can be used to predict the spatiotemporal spread of infectious diseases such as COVID-19. Based on our analyses, we anticipate cases to be reported in Saudi Arabia and Indonesia; additionally, countries with a moderate to low IDVI (*i.e.* ≤0.7) such as Indonesia, Pakistan, and Turkey should be on high alert and develop COVID-19 response plans as soon as permitting.

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Introduction

On December 30, 2019, pneumonia cases of unknown etiological origin were reported in Wuhan, China (WHO, 2020a). We now know that these cases were due to a coronavirus (*i.e.* Severe Acute Respiratory Syndrome Coronavirus 2 [SARS-CoV-2]); the disease has been named coronavirus disease 2019 (COVID-19).

Coronaviruses are RNA viruses distributed broadly among humans, other mammals, and birds. Six coronavirus species are known to cause human disease (Su *et al.*, 2016). Although most coronavirus infections are considered mild, two coronaviruses—Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV) and Middle East Respiratory Syndrome Coronavirus (MERS-CoV)—resulted in 10,590 cumulative cases in the past two decades, with mortality rates of 9.6% and 34.4%, respectively (WHO, 2003; WHO, 2019). As with SARS-CoV and MERS-CoV, SARS-CoV-2 is probably of zoonotic origin and human-to-human transmission has been confirmed (Chan *et al.*, 2020). Early studies of hospitalized patients with confirmed COVID-19 reported that severe illness was seen in 32% of cases and case fatality rates ranged between 11–15% (Huang *et al*., 2020); as more cases became confirmed some of these figures have been revised downwards (Wu *et al*., 2020). On January 30, 2020, WHO declared COVID-19 a public health emergency of international concern (WHO, 2020d). At that time, there had been 8,235 (8,124 [98.7%] in China) confirmed cases of COVID-19, including 171 deaths. Cases had been reported in Wuhan and 31 other provinces in China, as well as in 18 countries, including the Philippines, Sri Lanka, France, Germany, Finland, Canada, and the USA (WHO, 2020c; Kraemer, 2020). Following the rapid spread of cases within China, the Chinese authorities decided on January 23, 2020, to ban travel from and to Wuhan.

Given the potential of SARS-CoV, MERS-CoV, and other viruses to rapidly spread nationally and globally by commercial air travel (Findlater *et al*., 2018) we sought to characterize the possible spatiotemporal spread of COVID-19 during the first period of the outbreak by applying human mobility models and estimates derived from user activity of the social media platform Twitter. The objective of this study was to show how geolocated Twitter data allows to predict the spatiotemporal spread of infectious disease agents such as SARS-CoV-2 and to rapidly identify geographies at high risk of SARS-CoV-2 introduction.

Methods

This observational study analyzes the movement of people from Wuhan and the global spread of SARS-CoV-2 until January 30, 2020. This cut-off was used because at that time two main events happened which would affect SARS-CoV-2 spread: Wuhan was de facto quarantined by Chinese authorities and WHO declared COVID-19 a public health emergency of international concern. We therefore assumed that most of the COVID-19 cases reported outside China were linked to exposure that originally had occurred in Wuhan.

Epidemiological data

We used publicly available COVID-19 case data and aggregated to the town level (population > 50,000 people) on a weekly basis from December 31, 2019, to January 30, 2020 (Kraemer, 2020).

In total, 8,235 confirmed cases recorded at the global level by January 30, 2020, were included in our analyses. Data on a country's Infectious Disease Vulnerability Index (IDVI) was obtained from Moore *et al*. 2017; the IDVI is a validated metric of a country's capacity to prepare for and respond to infectious disease threats.

Human mobility data and analytical approach

We applied an analytical approach previously used to study urban transmission dynamics of dengue (Kraemer *et al*., 2018). Briefly, we used a convenience sample of openly available Twitter data from 2013–2015 to estimate human mobility patterns in 2019–2020 in Wuhan; the data was already cleaned and ready to be analyzed, and—given the unfolding COVID-19 pandemic—we felt it was important to be able to share our analyses in a timely manner. Also, at a global scale mobility has shown to be fairly sta-

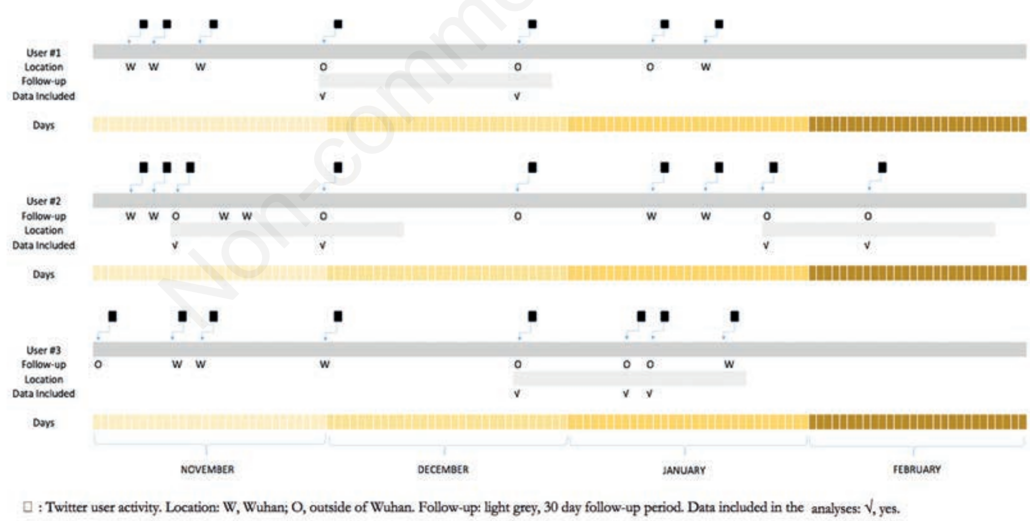

Figure 1. Analytical approach with Twitter activity of three illustrative users. Obtained Twitter database was filtered to only include users who posted at least two tweets on consecutive days within the city of Wuhan between November 1, 2013, and January 28, 2014, and November 1, 2014, and January 28, 2015, to ensure that the user was physically in Wuhan for at least 24 hrs. To characterize the possible spatiotemporal global spread of SARS-CoV-2, we then followed-up the Twitter activity of these users for 30 days post second tweet (*i.e.* up to February 28 of either 2014 or 2015) and determined whether these users travelled outside of Wuhan; we chose this 30-day follow-up period as we presumed that it would cover any COVID-19 pre-patent period if exposure would have happened prior to the users' second tweet. Using the geographic fingerprint of users' tweets, we estimated the locations visited by each user included in the study cohort by linking all tweets to the closest city. For movement of users within China, we also calculated the mean distance from Wuhan by averaging the maximum distance of each user based on their Twitter activity and the geographic fingerprint of their tweets. We used the Wilcoxon's rank test to compare the distance of visited locations and major airports connected to Wuhan from confirmed COVID-19 cases with known location (significance threshold set to p<0.05). See illustrative examples of Twitter users in the figure, showing the Twitter activity, their respective location when tweeting, and the geotagged Twitter data that was included in our analyses.

ble over long periods of time (Schneider *et al*., 2013). Our database consists of global tweets (spatial search windows: latitude –90 to 90 latitude and -180 to 180 longitude) posted from November 1, 2013, to February 28, 2014, and from November 1, 2014, to February 28, 2015. Human mobility patterns were then estimated by analyzing the data from Twitter users who had: i) tweeted at least twice on consecutive days from Wuhan, China, between November 1, 2013, and January 28, 2014, and November 1, 2014, and January 28, 2015 (*i.e.* the possible exposure to SARS-CoV-2); and ii) left Wuhan following their second tweet during the time period under investigation (*i.e.* the possible spread of SARS-CoV-2 following exposure in Wuhan). The time period was chosen as it represents the months that the current SARS-CoV-2 outbreak occurred over until travel outside of Wuhan became severely restricted due to the quarantine imposed by the Chinese authorities; the period also includes a 30-day follow-up period covering any COVID-19 pre-patent period if exposure would have happened prior to the users' second tweet in Wuhan by January 28 .

Table 1. Locations visited by the study cohort of Twitter users who were followed-up for 30 days after having tweeted at least two times on consecutive days from Wuhan between November 1, 2013, and February 28, 2014, and November 1, 2014, and February 28, 2015. The table reports: (1) the visited countries; (2) the number of cohort users traveling within the identified country; (3) the number of major cities (population > 50,000 people) visited by cohort users in each identified country; (4) the country IDVI; and (5) the date of first COVID-19 case reported up to one day after the declaration of public health emergency (30th January 2020).

Country	Number of users	Visited cities		IDVI	Date of first COVID-19 case reporteda
China	135	157	[Not listed]	0.663	December 30, 2019
USA	10	16	Allen, Atlanta, Chicago, Houston, Grand Prairie, Los Angeles, Mesquite, New York, Palo Alto, Pasadena, Richardson, San Diego, Santa Monica, San Mateo, Toledo, Washington DC	0.924	January 16, 2020
Saudi Arabia	7	4	Al-Madinah, Jiddah, Mecca, Riyadh	0.736	/
Thailand	7	8	Ayutthaya, Bangkok, Khlong Luang, Lam Luk Ka, Pak Kret, Phra Pradaeng, Samut Prakan, Saraburi	0.713	January 5, 2020
Australia	6	5	Brisbane, Geelong, Gold Coast, Melbourne, Sydney	0.912	January 15, 2020
Japan	5	20	Akita, Aomori, Beppu, Chitose, Dazaifu, Hachioji, Hakodate, Hino, Iwamizawa, Kitahiroshima, Musashino, Nagaoka, Oita, Saga, Sagamihara, Sakata, Sapporo, Tokyo, Tomakomai, Tomisato	0.926	January 3, 2020
UK	5	9	Cheadle, Doncaster, Edinburgh, Esher-Molesey, London, Manchester, Sheffield, Staines, Woking-Byfleet	0.89 0.761	January 31, 2020 January 25, 2020*
Malaysia	4	9	Banting, George Town, Kajang-Sungai Chua, Klang, Kuala Lumpur, Petaling Jaya, Seremban, Subang Jaya, Sungai Ara		
Canada	3	5	Edmonton, Hamilton, Saint Catharines-Niagara, Toronto, Vancouver	0.973	January 22, 2020
Indonesia	3	8	Bandung, Ciamis, Cibeureum, Kadungora, Klaten, Sukabumi, Tangerang, Tasikmalaya	0.562	/
Singapore	3	1	Singapore	0.877	January 21, 2020
Barbados	1	1	Bridgetown	0.681	/
Brazil	1	7	Cacapava, Caieiras, Cotia, Diadema, Franco da Rocha, Guarulhos, Sao Paulo	0.716	/
Cambodia	1	1	Siem Reap	0.355	January 26, 2020
France	1	1	Paris	0.855	January 18, 2020
India	1	1	Bommanahalli	0.499	January 30, 2020*
Ireland	1	2	Dublin, Limerick	0.906	/
Italy	1	2	Modena, Verona	0.821	January 31, 2020
Mexico	1	1	Mexicali	0.734	/
New Zealand	1	3	Auckland, Christchurch, Wellington	0.916	/
Pakistan	1	2	Faisalabad, Lahore	0.308	/
Philippines	1	1	Davao	0.544	January 30, 2020*
Puerto Rico	1	2	Carolina, San Juan	0.924	/
Spain	1	3	Barakaldo, Bilbao, Getxo	0.875	January 31, 2020
Taiwan	1	1	Taichung	0.709	/
Turkey	1	4	Bozuyuk, Eskisehir, Istanbul, Sultanbeyli	0.677	/
United Arab Emirates	1	1	Dubai	0.765	January 29, 2020*
Vietnam	1	1	Ho Chi Min City	0.626	January 17, 2020

'/' no reported cases; a the date of onset symptoms; *confirmation date; IDVI, infectious disease vulnerability index

Our analytical approach is further illustrated in Figure 1. Each tweet has a unique user ID, latitude, longitude, and date (year, month, hour, second). Obtained Twitter data is restricted to 1% of tweets posted globally during that time period (Kraemer *et al.*, 2018); as previously shown, the amount of Twitter users with geo-located information would have represented 1% of the total global population in the study period (Schneider *et al.*, 2013).

Results

During the time window selected to estimate people movement

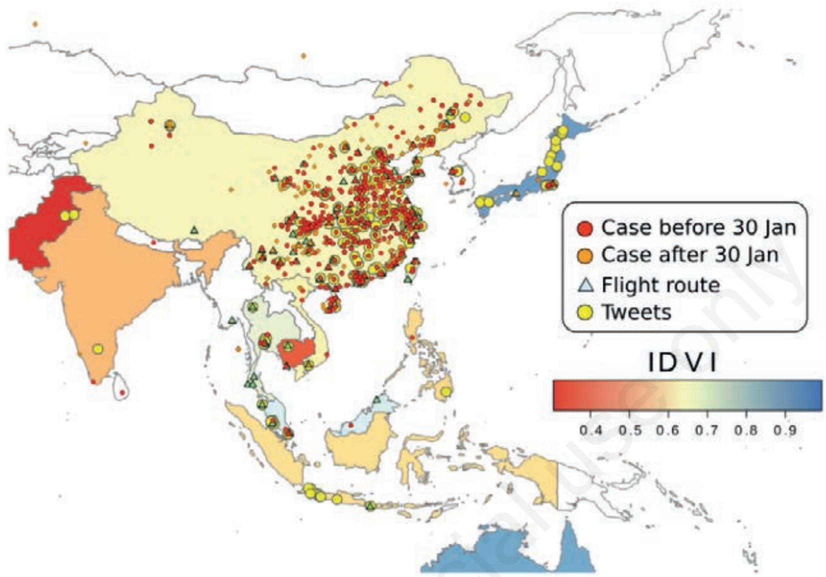

Figure 2. South East Asia locations visited by the study cohort of Twitter users who were followed-up for 30 days after having tweeted at least two times on consecutive days from Wuhan between November 1, 2013, and February 28, 2014, and November 1, 2014, and February 28, 2015. The figure includes airports with scheduled flights from Wuhan; locations of reported COVID-19 cases by January 30, 2020; and IDVI of countries visited by the study cohort.

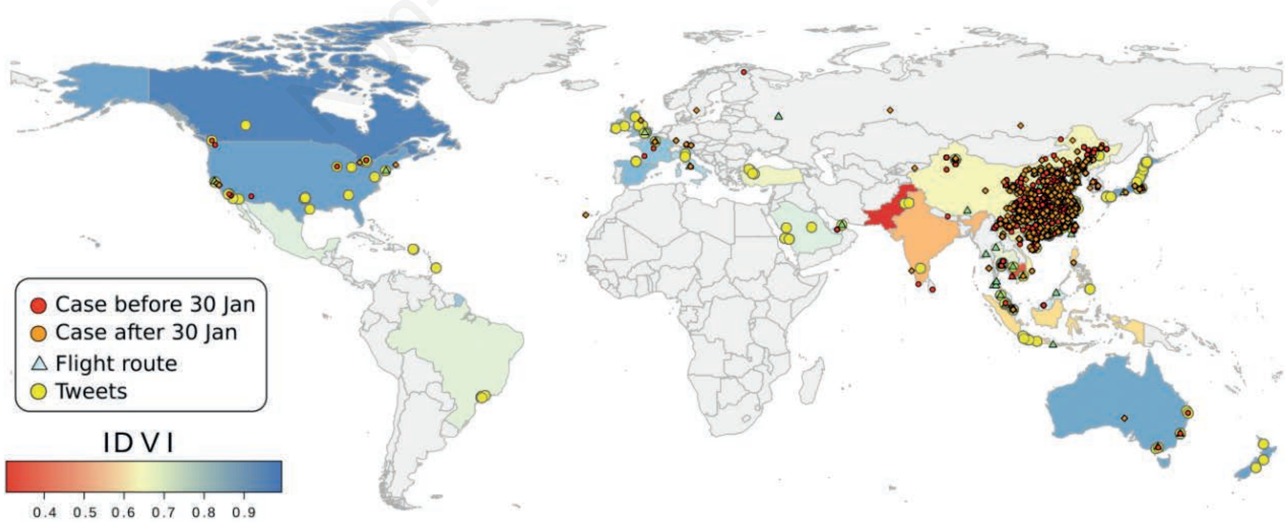

Figure 3. Location visited by visited by the study cohort of Twitter users who were followed-up for 30 days after having tweeted at least two times on consecutive days from Wuhan between November 1, 2013, and February 28, 2014 and November 1, 2014, and February 28, 2015. The figure includes airports with scheduled flights from Wuhan; locations reporting SARS-CoV-2 cases by January 30, 2020; and IDVI of countries visited by the study cohort.

(*i.e*. November 1, 2013 to February 28, 2014, and November 1, 2014 to February 28, 2015), the number of Twitter users who posted tweets from Wuhan was 1,344 for a total 313,286 geolocated tweets (median = 6, interquartile range [IQR] = 1–30). Among the selected users, 307 (22.8%) posted tweets in locations outside Wuhan (24,649 [7.9%] tweets; median = 10; IQR= 3–38), with 161 users (12.0%) posting more than two tweets from Wuhan between November 1 and January 28—our study cohort. Of these users, 133 (82.6%) posted tweets from 157 Chinese cities (1,344 [71.9%] tweets) during the 30 days after leaving Wuhan following their second tweet (Figure 2, Table 1), with a median of 2 (IQR= 1–3) locations visited and a mean distance of 601 km (IQR= 295.2–834.7 km) traveled. The most visited cities were Beijing (29 users, 18%), Shanghai (29 users, 18%), Guangzhou (25 users, 15.5%), and Nanjing (11 users, 6.8%).

As per Twitter activity of our user study cohort, 60 (37.2%) traveled abroad to a total 119 locations in 28 countries (Figure 3, Table 1). The countries with the highest number of visiting users were the USA (10, 16.3%), Thailand (7, 11.4%), Saudi Arabia (7, 11.4%), and Australia (6, 9.8%) (Table 1). The most visited cities were Bangkok (7 users), Mecca (5 users), London (5 users), Sydney (4 users), Kuala Lumpur (4 users), and Los Angeles (4 users); 15 users (25%) visited more than one city, with two users reaching a maximum of 5 cities visited. For those COVID-19 cases reported by January 30, 2020, for which the city was available, we compared the distance to the locations visited by our study cohort and the airports connected to Wuhan. Locations visited by our cohort users were statistically closer to reported cases than airports with the median distance being 20.1 km (IQR= 3.6–95.4 km) and 75.9 km (IQR=25.1–187.8 km), respectively (Wilcoxon's rank test, $p<0.01$). Of the 82 cases reported outside China, 54 cases had known coordinates and 74.1% (40 cases) were reported less than 15 km (median = 7.4 km, IQR= 2.9–285.5 km) from a location visited by at least one of our cohort's users.

The countries visited by the cohort's users and which have cases reported by January 30, 2020, have a median IDVI equal to 0.74 (IQR = 0.67–0.89) (Table 1). In total, 14 countries (50%) outside China visited by the cohort's users have reported cases. Among the 10 countries visited by more than one user, 7 reported multiple cases before January 26, 2020 (Table 1).

Discussion

Using an analytical approach that has previously been used to understand local spread dynamics of dengue (Kraemer *et al*., 2018), we sought to characterize the spatiotemporal spread of SARS-CoV-2. We decided to use geolocated tweets instead of data already used to predict SARS-CoV-2 spread such as flights, census surveys, internet traffic, and mobile phone activity(Lai *et al*., 2020), as these approaches do not necessarily allow to identify travelers' intermediate or final destinations (*e.g*. flight data only capture the flight route but not visited cities; mobile phone data do not capture overseas trips).

Based on 2013–2014 and 2014–2015 Twitter user data, and given that major travel routes only marginally changed during the last 5 years, we analyzed the mobility of a cohort of people who had i) tweeted at least twice from Wuhan between November 1 and January 28; and ii) left Wuhan between November 1 and January 28 following their second tweet. Our findings show that human mobility of these Twitter users is substantial, with a defined study cohort of 161 users travelling outside of Wuhan. Of these, 133 travelled to 157 locations in China and 60 travelled to 119 locations in 28 countries. Of the 157 locations within China, 87 (55.4%) had—as of January 30, 2019—reported confirmed cases; of the 5,930 COVID-19 cases with known location reported within China, 4,176 (70.4%) occurred in a location visited by at least one of our cohort's users. Of the 119 overseas locations, 15 (12.6%) had—as of January 30, 2019—reported confirmed cases; similarly, of the 54 COVID-19 cases reported outside China with known location, 40 (74.1%) occurred in locations visited by at least one of our cohort's users.

During the week after January 30, 2020, first reporting of COVID-19 cases occurred in 5 additional countries. Among these newly reporting countries, we predicted that SARS-CoV-2 would spread to United Kingdom (January 31), Spain (January 31), and Italy (January 31) (Table 1); Sweden (January 31) and Russia (January 31) were not identified by our analyses.

Limitations

A limitation of our study is that using geolocated Twitter data to model human mobility could be biased towards a population that has access to a smartphone and use of the application; while this may be true, we note that the same population is also likely to have greater economic means for mid -and long-distance travel, a critical factor if assessing the global spread of an infectious disease agent such as SARS-CoV-2. It is also likely that access to smartphones and Twitter since 2015 by the population in Wuhan may have changed, but it is less clear whether the human mobility patterns would have changed significantly—an issue which needs further investigation.

Conclusion

On January 30, 2020, WHO declared COVID-19 to be a public health emergency of international concern (WHO, 2020d). The response to contain the COVID-19 outbreak has been evolving daily since then: in China several major cities were quarantined for weeks, with severe limitations on people's movements; internationally, airlines cancelled flights to China and countries (*e.g*., USA, United Kingdom, Italy) evacuated their nationals as well as screening travelers coming from China at major ports of entry. On March 11, WHO declared COVID-19 a pandemic. As of April 21, 2020, 2,314,621 confirmed confirmed cases of COVID-19 have been reported, including 157,847 deaths, in 210 countries (WHO, 2020b).

Based on our analyses, we anticipated that several locations that had yet to report COVID-19 cases by January 30, 2020, were expected to have cases or report cases soon (Table 1). Of immediate concern for outbreak containment were—besides all identified cities in China—locations in countries in Central and South East Asia, *i.e*. cities that were easily accessible via direct flights, by road or sea from Wuhan and other Chinese cities (Table 1). Globally, we anticipated cases to be reported in early February in Saudi Arabia and Indonesia, all countries where more than one user from our study cohort travelled to within 30 days after having tweeted a second time from Wuhan during our study period; additionally, countries with a moderate to low IDVI (*i.e*. ≤0.7) such as Indonesia, Pakistan, and Turkey should have been on high alert and develop COVID-19 response plans as soon as permitting. Surprisingly, our map did not identify users who travelled to Africa. This result highlighted a possible low probability of importation of the virus there during the early phases of the outbreak. Although many suspected cases had been tested, until February 26, 2020, no confirmed COVID-19 case had been reported in Africa.

The results of our study show that geolocated Twitter data can be used to describe human mobility and the possible spread of a novel disease agent such as SARS-CoV-2. Moreover, such approach could be used to predict spread within countries once initial introduction has occurred. Twitter data could also be merged with other data that capture human movement (*e.g*., flight traffic, mobile phone, and census data) to create a global and local alert system to improve the international and national response to novel public health treats such as SARS-CoV-2.

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