Population mobility patterns and early phases of the COVID-19 pandemic in Indonesia

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Abstract. Understanding population mobility could facilitate the intervention to prevent the rapid geographical spread of emerging infectious diseases. Here we describe how the patterns of population mobility can be associated with the number of COVID-19 cases and, therefore, could be used to develop a simulation for the potential path of disease spreading. Our analysis of country-scale population mobility networks is based on a proxy network from social media, which we incorporated in a model to reproduce the spatial spread of the early stage COVID-19 epidemic in Indonesia.

Introduction

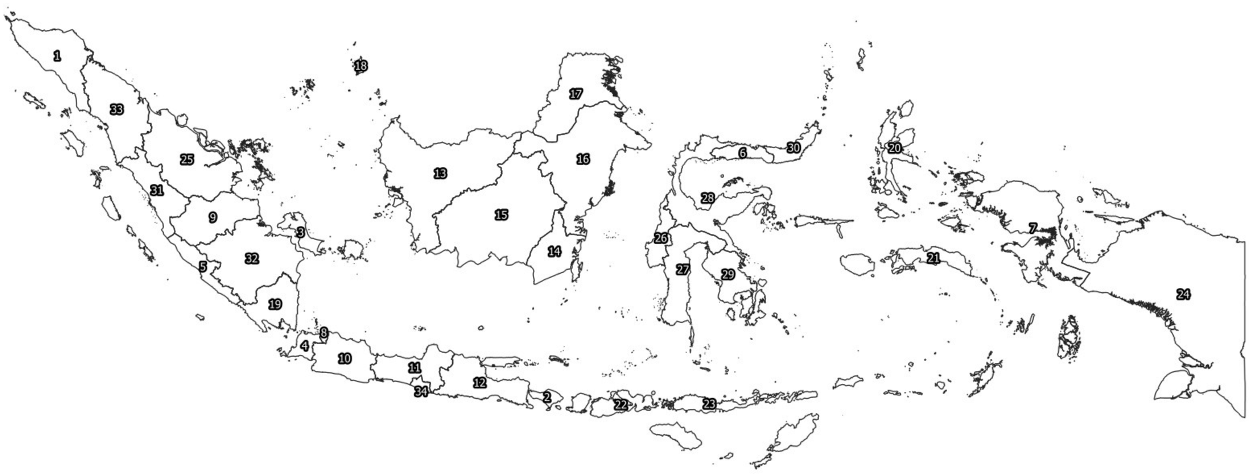
In March 2020, COVID-19 was declared as a global pandemic and has been threatening public health since. Starting in Wuhan, China, the pandemic has spread rapidly to other countries, and the population movement among countries could be one of the important triggers [1]. In Indonesia, the first confirmed two cases of COVID-19 infection was reported in early March [2] and since then has been spread to the entire 34 provinces.

Population mobility plays a crucial role in the temporal and spatial spreading of infectious diseases [3], given that infections transported through the mobility may initiate or facilitate epidemics [6]. Consequently, understanding population mobility patterns becomes crucial for disease prediction.

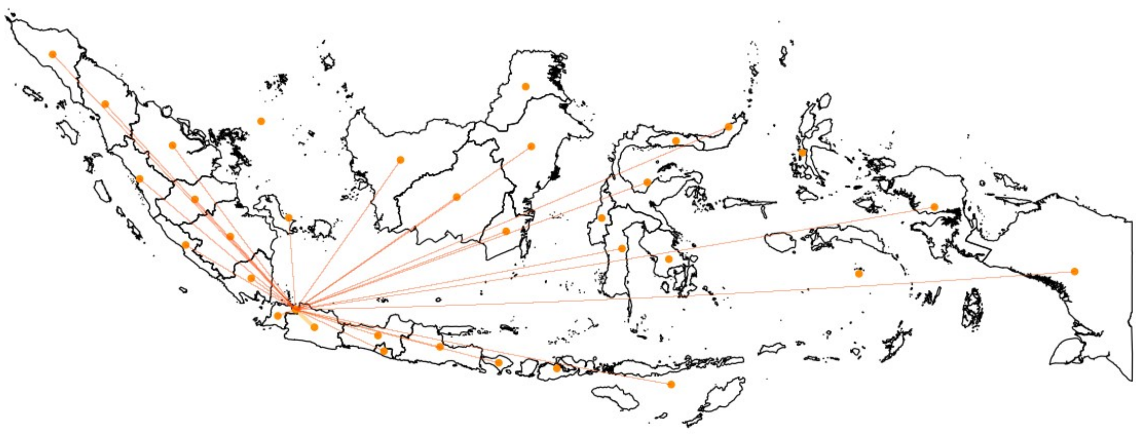
The presence of location-sharing services made it possible for researchers to gain unprecedented access to the direct records of human activity [5]. Twitter can be used as a proxy for tracking and predicting human movement, and it has been demonstrated as a reliable source for studying human mobility patterns [4]. This study investigated the potential of using geotagged Twitter data in Indonesia to reveal the level of connectedness among provinces that later may provide early signals to detect or predict the upcoming potential outbreak location.

Methods

We obtained COVID-19 cases for provinces in Indonesia in April 2020 from Kawal COVID-19. We complemented COVID-19 surveillance data with geotagged tweets posted in the provincial administrative boundaries of the study area from January-December 2019 as the baseline period for mobility patterns. We employed Twitter's Application Programming Interface and selected Tweets within Indonesia's boundaries for analysis to achieve this. We only extracted the user identification string, timestamp, and longitude and latitude of the user's location in the Tweets. Subsequently, we overlaid the geotagged tweets on the provincial administrative map of the study area and exchanged the geocode to the province identification number (Fig 1.a.).



(a)



(b)

Fig 1. (a) The Provincial Administrative Identification Number;
(b) The frequency of human mobility from DKI Jakarta to the 33 other provinces.

We formulated an algorithm to estimate the frequency of mobility among 34 provinces in Indonesia. The frequency was calculated based on Twitter users' mobility patterns between pairs of provinces. The mobility patterns were computed by estimating the rate with which a Twitter user in one province re-tweeted in another province within the same month. To assess the association between human mobility and COVID-19 cases, we only consider the frequency of mobility out of DKI Jakarta to the 33 other provinces (Fig 1.b.).

Results and Discussion

The total number of COVID-19 cases in 33 provinces, not including DKI Jakarta, in our analysis was 4,008, with the highest cases were reported from Jawa Barat. All three most contributed cases came from provinces in Java Island, as the nearest provinces from DKI Jakarta. Most of the mobility (83%) from DKI Jakarta was to the other 5 provinces in Java Island, respectively, Jawa Barat, Banten, Jawa Timur, Jawa Tengah, and DI Yogyakarta (Tabel 1).

We identified that the rate of population mobility from DKI Jakarta to a province was closely associated with the number of COVID-19 cases in the province (Fig 2). Therefore, we propose that it could be used as a proximal indicator to predict future outbreaks. Later, it could inform proactive nonpharmaceutical interventions for disease control, such as resource relocations to curb disease outbreaks and negative influences [7].

Our results suggest that mobility patterns obtained from Twitter data are amenable to reflect the mobility dynamics in the COVID-19 pandemic quantitatively. Therefore, this study's methodological knowledge seed future applications of the easily accessible Twitter data in monitoring mobility dynamics [8]. Understanding human mobility in the early stages of a pandemic is crucial for assessing travel patterns to prevent disease spread [9]. Our results suggest that population mobility could be one of the important drivers of the spread of COVID-19 from the hotspot area to other areas, and the geotagged Twitter data can provide essential information on population mobility patterns to improve our understanding of the direction and the risk of the spread of diseases. In summary, our findings can provide useful information for developing more efficient early warning and response systems.

Tabel 1. The frequency of mobility out of DKI Jakarta to the 33 other provinces In Indonesia

asal	tujuan	frekuensi baseline (Jan-Dec 2019)	Jumlah Kasus per 22 Maret 2020
DKI Jakarta	Jawa Barat	0.43573	762
DKI Jakarta	Banten	0.18893	337
DKI Jakarta	Jawa Timur	0.08656	638
DKI Jakarta	Jawa Tengah	0.07625	479
DKI Jakarta	DI Yogyakarta	0.04321	75
DKI Jakarta	Bali	0.03543	152
DKI Jakarta	Kalimantan Tengah	0.01864	82
DKI Jakarta	Sumatera Utara	0.01587	93
DKI Jakarta	Sulawesi Selatan	0.01042	387
DKI Jakarta	Lampung	0.01021	27
DKI Jakarta	Sumatera Selatan	0.00805	89
DKI Jakarta	Kalimantan Timur	0.00725	69
DKI Jakarta	Sumatera Barat	0.00675	81
DKI Jakarta	Nusa Tenggara Timur	0.00583	1
DKI Jakarta	Riau	0.00561	35
DKI Jakarta	Nusa Tenggara Barat	0.00486	108
DKI Jakarta	Kepulauan Riau	0.00481	81
DKI Jakarta	Kalimantan Selatan	0.00466	107
DKI Jakarta	Kalimantan Barat	0.00451	31
DKI Jakarta	Aceh	0.00412	7
DKI Jakarta	Bangka-Belitung	0.00412	8
DKI Jakarta	Sulawesi Utara	0.00325	20
DKI Jakarta	Jambi	0.00242	13
DKI Jakarta	Sulawesi Tengah	0.00196	29
DKI Jakarta	Papua	0.00192	123
DKI Jakarta	Sulawesi Tenggara	0.00171	37
DKI Jakarta	Maluku	0.00170	17
DKI Jakarta	Papua Barat	0.00141	8
DKI Jakarta	Bengkulu	0.00138	8
DKI Jakarta	Gorontalo	0.00100	7
DKI Jakarta	Maluku Utara	0.00087	12
DKI Jakarta	Sulawesi Barat	0.00030	8
DKI Jakarta	Kalimantan Utara	0.00027	77

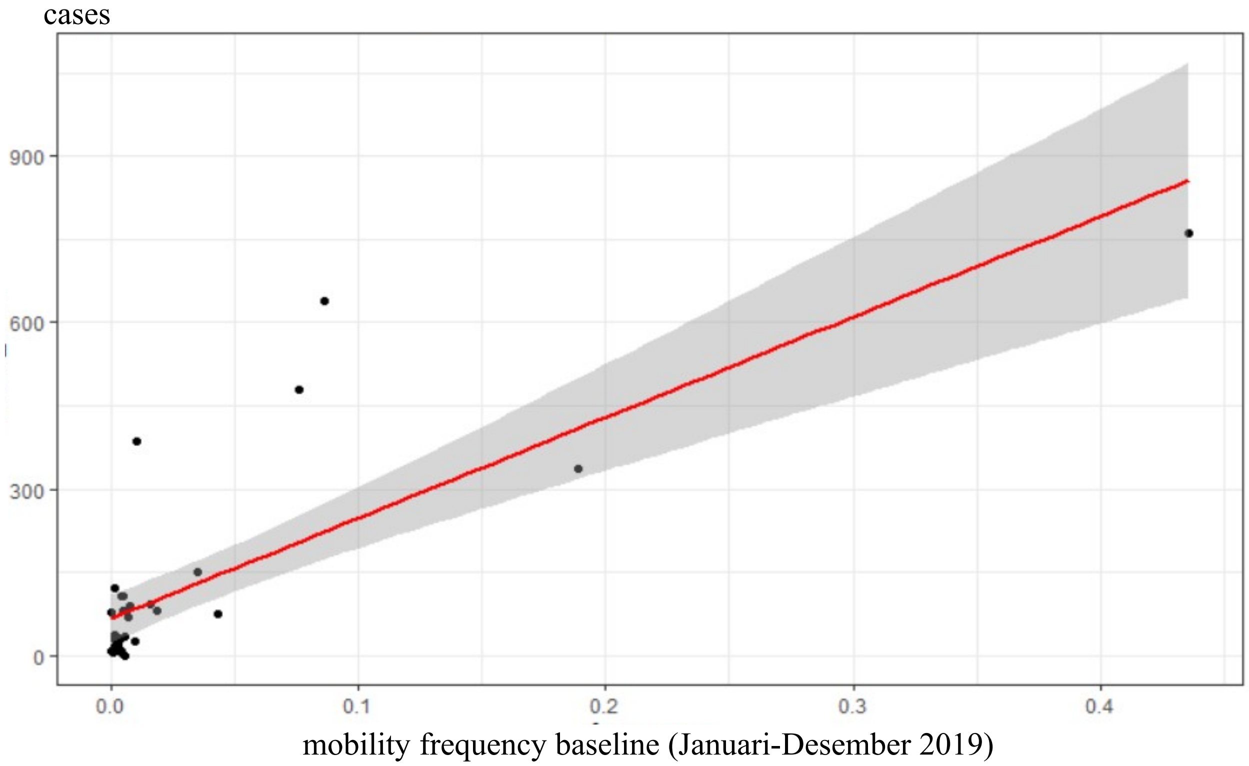


Fig 2. The association between the frequency of population mobility out of DKI Jakarta to the 33 other provinces and the number of COVID-19 cases (Adj R2 = 0.62; intercept = 66.5; slope = 1813.5; P = 3.83e-08)

References

[1] A. M. Y. Chu, A. Tiwari, and M. K. P. So, "Detecting early signals of COVID-19 global pandemic from network density," *J. Travel Med.*, vol. 27, no. 5, p. taaa084, Aug. 2020, doi: 10.1093/jtm/taaa084.

[2] R. Djalante *et al.*, "Review and analysis of current responses to COVID-19 in Indonesia: Period of January to March 2020," *Prog. Disaster Sci.*, vol. 6, p. 100091, Apr. 2020, doi: 10.1016/j.pdisas.2020.100091.

[3] S. Changruenngam, D. J. Bicout, and C. Modchang, "How the individual human mobility spatio-temporally shapes the disease transmission dynamics," *Sci. Rep.*, vol. 10, no. 1, Dec. 2020, doi: 10.1038/s41598-020-68230-9.

[4] R. Jurdak, K. Zhao, J. Liu, M. AbouJaoude, M. Cameron, and D. Newth, "Understanding human mobility from Twitter," *PLoS ONE*, vol. 10, no. 7, pp. 1–16, 2015, doi: 10.1371/journal.pone.0131469.

[5] B. Hawelka, I. Sitko, E. Beinat, S. Sobolevsky, P. Kazakopoulos, and C. Ratti, "Geo-located Twitter as proxy for global mobility patterns," *Cartogr. Geogr. Inf. Sci.*, vol. 41, no. 3, pp. 260–271, May 2014, doi: 10.1080/15230406.2014.890072.

[6] A. Findlater and I. I. Bogoch, "Human Mobility and the Global Spread of Infectious Diseases: A Focus on Air Travel," *Trends Parasitol.*, vol. 34, no. 9, pp. 772–783, Sep. 2018, doi: 10.1016/j.pt.2018.07.004.

[7] C. Zeng *et al.*, “Spatial-Temporal Relationship Between Population Mobility and COVID-19 Outbreaks in South Carolina: Time Series Forecasting Analysis,” *J. Med. Internet Res.*, vol. 23, no. 4, p. e27045, Apr. 2021, doi: 10.2196/27045.
[8] X. Huang, Z. Li, Y. Jiang, X. Li, and D. Porter, “Twitter reveals human mobility dynamics during the COVID-19 pandemic,” *PLOS ONE*, vol. 15, no. 11, p. e0241957, Nov. 2020, doi: 10.1371/journal.pone.0241957.
[9] LSHTM CMMID COVID-19 working group *et al.*, “Changing travel patterns in China during the early stages of the COVID-19 pandemic,” *Nat. Commun.*, vol. 11, no. 1, p. 5012, Dec. 2020, doi: 10.1038/s41467-020-18783-0.