Twitter-Based Activity Patterns:

A Case Study From Post-Circuit Breaker Singapore

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Contents

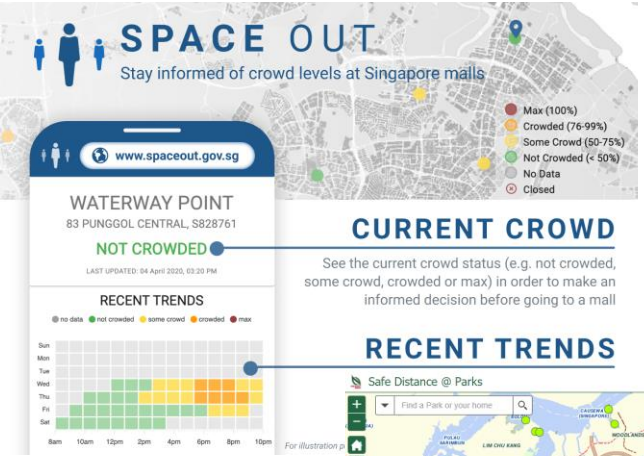
2.0 Introduction

2.0 Introduction

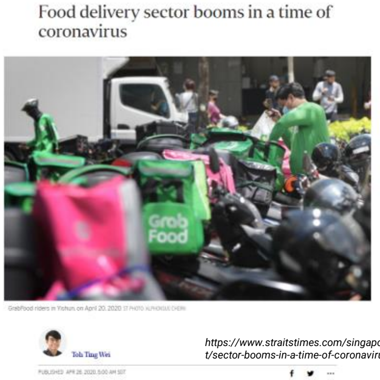
Singapore entered Phase 2 re-opening since 19 July 2020

- All residents advised to practice safe distancing, avoid crowded areas
- Businesses/agencies/institutions rolled out measures to facilitate safe usage of public spaces
- Fewer people visit F&B

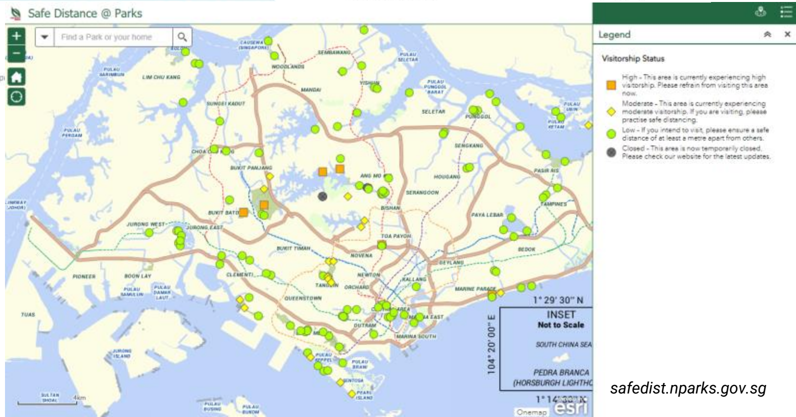
→ **Potential changes in place-visiting behaviours and activity patterns!**



ura.gov.sg



https://www.straitstimes.com/singapore/transport/sector-booms-in-a-time-of-coronavirus



safedist.nparks.gov.sg

Using Twitter Data to Study Activity Patterns

Location-based social media data increasingly used for urban science and GIS research:

- Rich attribute information (temporal, spatial, semantic), easy to obtain
- Study public sentiments, individual and aggregated activity-space, activity trajectory, location profiling and association
- COVID-related research: movement volume vs infection rates (Kabir and Madria, 2020)

Twitter-based research in Singapore

- Only a handful; mostly explored semantic information (public sentiment during elections)
- Rarely used geospatial aspect of Tweets

→ a valuable dataset that is not fully explored in the context of Singapore for geospatial research questions

Research Questions

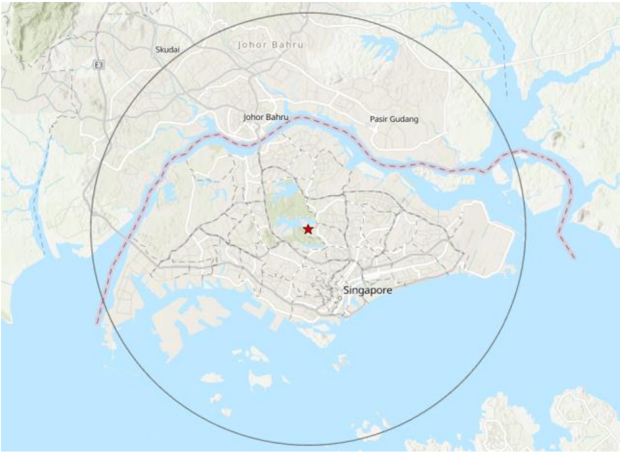
1. What are activity patterns like in a post-CB Singapore?
2. Are service amenities still important in attracting activities?
3. Are Twitter data suitable for geospatial research in Singapore?

3.0 Methodology

3.1 Data Collection

Tweets

- Twitter public API to search for all tweets posted from 18 Sep to 10 Oct 2020
- Spatial extent: 25 km radius from Central Catchment - covered most of Singapore main island



Note: unsuccessful data collection for some time periods(unstable network connection and search rate limit imposed by Twitter)

Date	Day of Week	Status
23 Sep 2020	Wednesday	Missing 9 hours (8 AM - 5 PM)
24 Sep 2020	Thursday	Missing 8 hours (8 AM - 4 PM)
27 Sep 2020	Sunday	Missing 6 hours (9 AM - 3 PM)
28 Sep 2020	Monday	Missing 11 hours (8 AM - 7 PM)
29 Sep 2020	Tuesday	Missing 12 hours (8 AM - 8 PM)
30 Sep 2020	Wednesday	Missing 13 hours (8 AM - 9 PM)
1 Oct 2020	Thursday	Missing 11 hours (8 AM - 7 PM)
2 Oct 2020	Friday	Missing 10 hours (8 AM - 6 PM)
3 Oct 2020	Saturday	Missing 10 hours (8 AM - 6 PM)
4 Oct 2020	Sunday	Missing 12 hours (8 AM - 8 PM)
5 Oct 2020	Monday	Missing 14 hours (8 AM - 10 PM)
6 Oct 2020	Tuesday	Missing 16 hours (8 AM - 12 AM)
8 Oct 2020	Thursday	Missing 15 hours (9 AM - 12 AM)
9 Oct 2020	Friday	Missing 22 hours (12 AM - 10 PM)
10 Oct 2020	Saturday	Missing 16 hours (9 AM - 12 AM)

3.1 Data Collection

Spatial Precision of Collected Tweets

- Tweets returned by Twitter API have varied levels of spatial precision based on the users' settings
- Tweets with:
  - Exact X/Y coordinates: digitised into point features directly
  - Specific landmark as place name: geocoded using OneMap search API
  - Spatial information at neighbourhood scale or above: not used

Type of Spatial Attributes (in decreasing order of precision)	**Percentage of Tweets**
With exact coordinates (X/Y)	0.25%
With place name (a specific landmark), but without X/Y coordinates	0.31%
With place name (a neighbourhood/town), but without X/Y coordinates	0.01%
With place name (a region), but without X/Y coordinates	2.43%
With place name (a city), but without X/Y coordinates	0.03%
With place name (a state/province), but without X/Y coordinates	0.00%
With place name (a country), but without X/Y coordinates	0.05%
No explicit spatial information	96.91%

3.1 Data Collection

Points of Interest (POI) and other Geospatial Data

- 12 types of service amenity POIs selected as explanatory variables
- Geospatial locations of POIs were collected from official government sources.

Data	Source
Hawker Centres Residential with 1st Storey Commercial Community Clubs Parks Park Connector Network Dual Use Scheme (DUS) Sports Facilities SCDP Park Mall Master Plan 2019	data.gov.sg
Shopping Malls	List of shopping malls in Singapore from Wikipedia (https://en.wikipedia.org/wiki/List_of_shopping_malls_in_Singapore) and geocoded using OneMap search API
MRT Stations Bus Stops Taxi Stands	mytransport.sg
Medical Facilities	KML file extracted from Google Maps

3.2 Spatiotemporal Analysis and Linear Regression Analysis

Exploratory Data Analysis

- To understand spatiotemporal activity patterns (framework adapted from Rao et al. (2012))

Ordinary Least Square (OLS) regression analysis

- Estimate relationship between aggregated tweet counts against the distance to the nearest service amenity POIs

	Temporal Analysis	**Spatial Analysis**	**Dynamic Spatiotemporal Analysis**	**Static Spatiotemporal Analysis**
Temporal Attribute	Independent	Fixed	Independent	Fixed
Spatial Attribute	Fixed	Independent	Dependent	Dependent
Thematic Attribute	Dependent	Dependent	Fixed	Fixed
Examples of questions for this study	In the same location, how do activity patterns vary with time?	In the same time period, how do activity patterns vary in places?	How do spatial patterns of activities vary with time?	How do spatial patterns vary in different locations at a fixed point of time?

3.3 Random Forest Model

Objective: model activity patterns in off-work recreational hours
Tool: ArcGIS Forest-Based Classification and Regression

An adaptation from Leo Breiman’s Random Forest Algorithm, which is a supervised machine learning model.

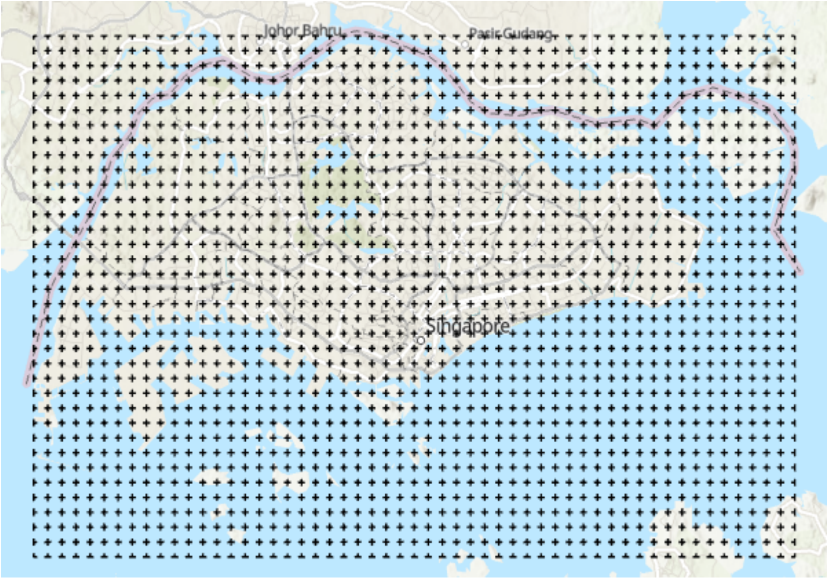
To train a model based on the number of tweets at different locations in Singapore, given a set of explanatory variables

3.3 Random Forest Model

Model Training Input layer :

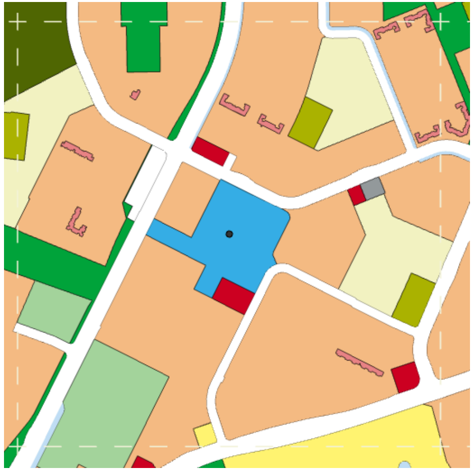
1. Fishnet Grid cells points (1kmx1km)

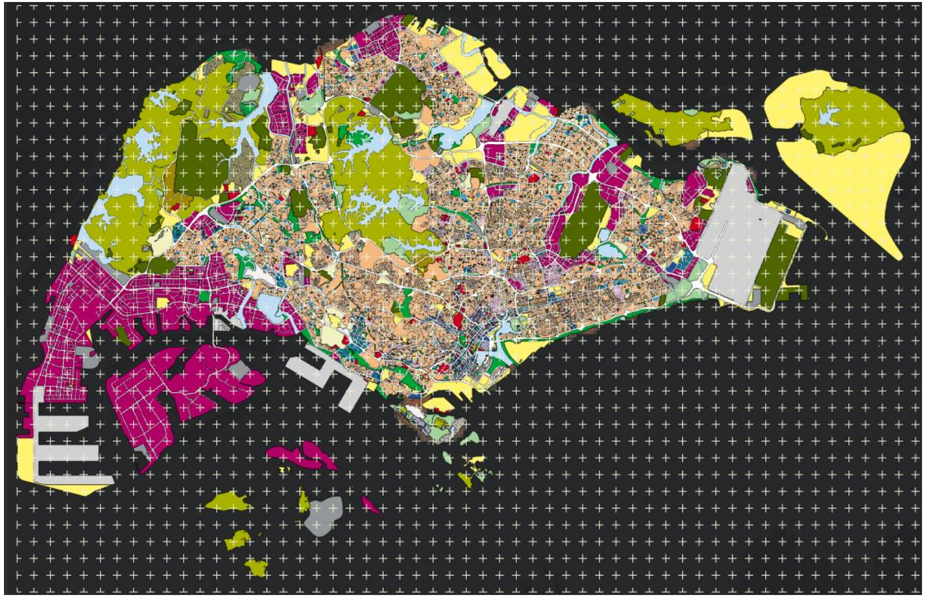
1. Attribute variables - land use mix type (Categorical) and total tweet counts



3.3 Random Forest Model

Extracting Land use mix type per fishnet grid cell in categorical fields (i.e. 1 or 0)



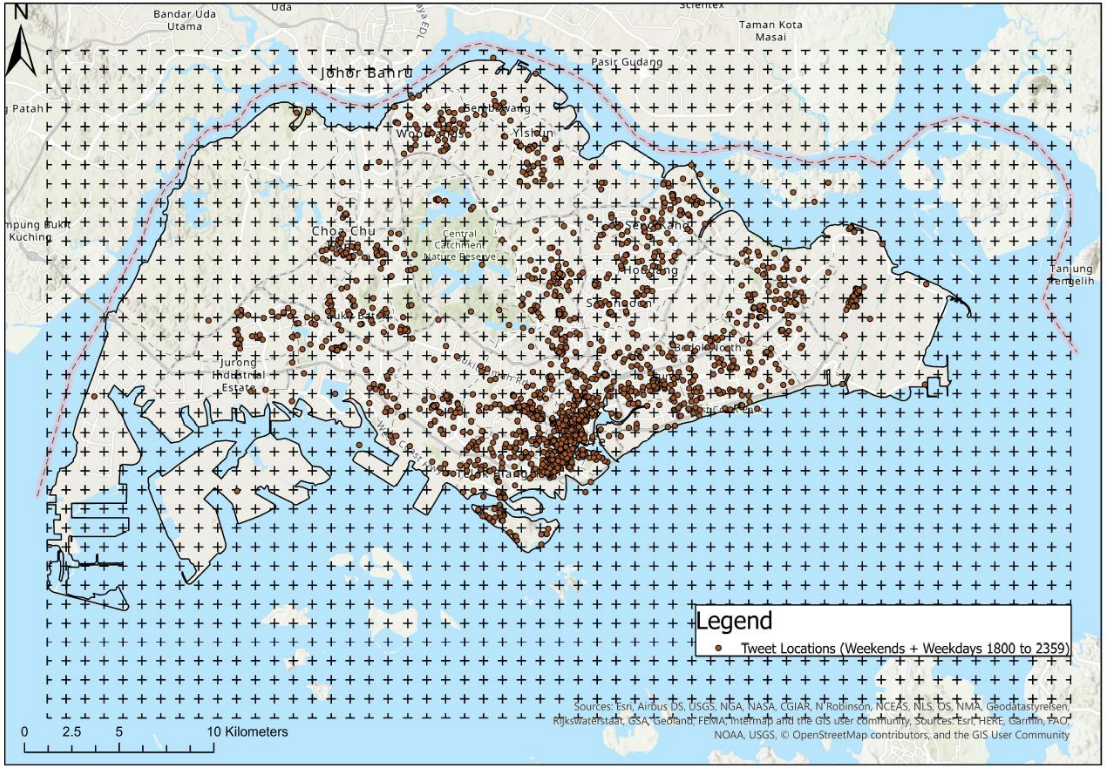


3.3 Random Forest Model

Extracting Total Tweet counts per fishnet grid cell via spatial join

Tweets are only from weekends and weekdays 1800 to 2359 hrs (non-working hours)

A total of 3982 tweets



3.3 Random Forest Model

Explanatory *distance* variables:

1. Shopping Malls - **Point layer**
2. Residential with 1st storey commercial (e.g. HDB shop houses) - **Point layer**
3. Parks - **Point layer**
4. SDCP park and mall public link - **Polygon layer**
5. Hawker Centres - **Point layer**
6. Park Connectors - **Polygon layer**
7. School Facilities - **Point layer**
8. Community Clubs - **Point layer**
9. Bus stop - **Point layer**
10. Mrt Stations - **Point layer**
11. Taxi stands - **Point layer**
12. Medical Facilities - **Point layer**

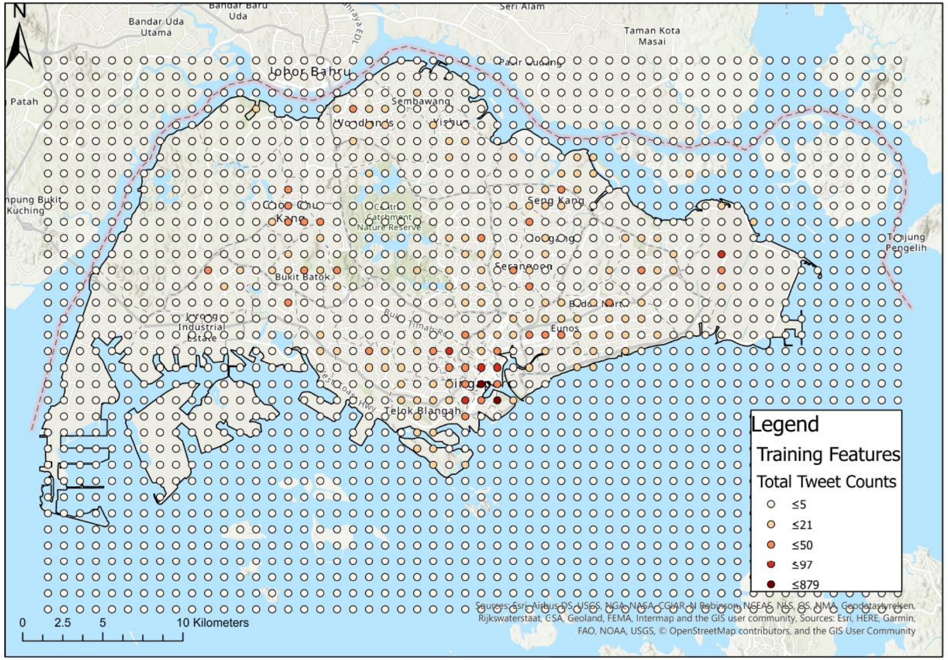
3.3 Random Forest Model

Model Parameters

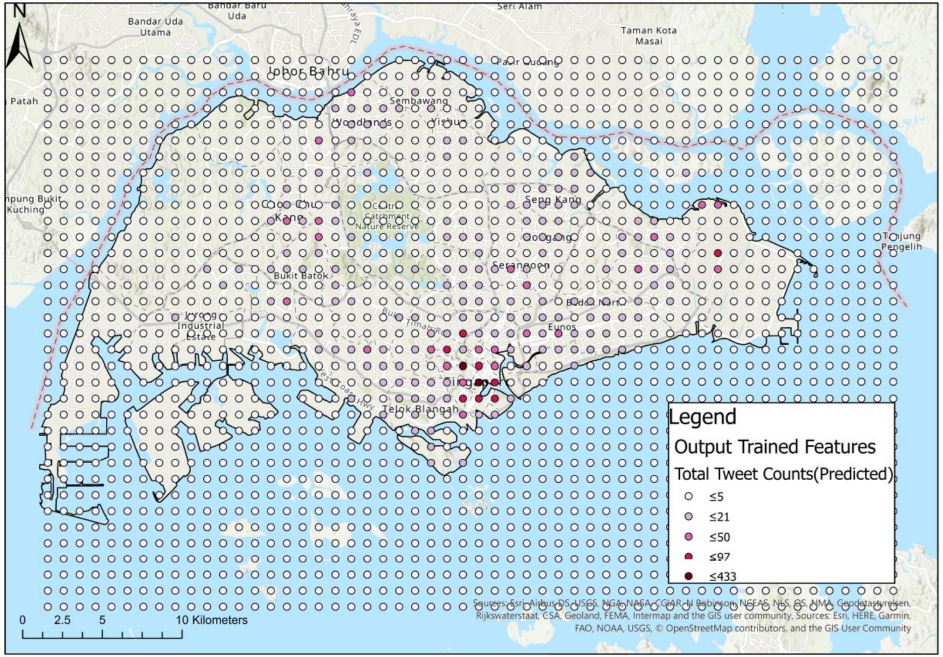
Number of Trees	500
Leaf Size	5
Tree Depth	11-26
Mean Tree Depth Range	16
% of Training Available per Tree	100
Number of Randomly Sampled Variables	8
% of Training Data Excluded for Validation	10

3.3 Random Forest Model

Model Training Input



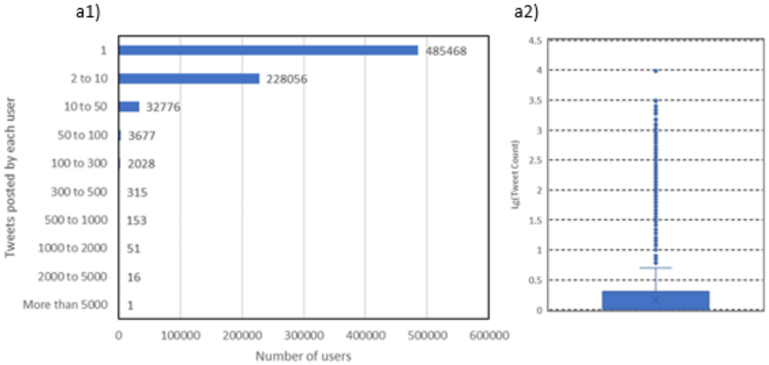
Model Trained Features Prediction



4.0 Result and Analysis

4.1 Twitter Users in the Study Area

All tweets collected



Geotagged tweets in Singapore

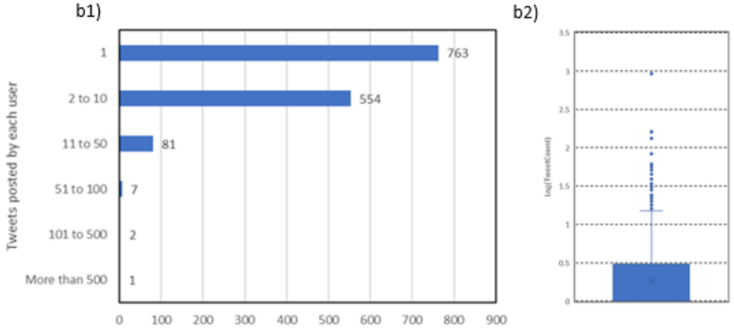
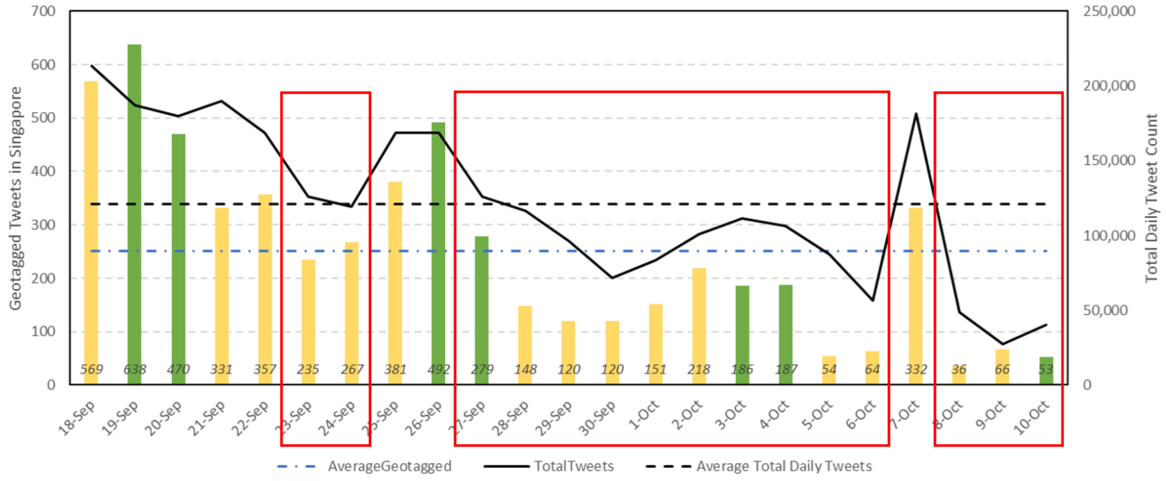


Figure 4.1. a) Distribution of all tweets (total tweets = 2,776,651, total user = 748,533, mean tweets/user = 3.71, median tweets/user = 1, sd = 25.46), b) Distribution of geotagged tweets in Singapore (total tweet count = 5,754, total user = 1,396, mean tweets/user = 4.12, median tweets/user = 1, sd = 25.87)

- Tweet counts by each user varied remarkably
- A large number of users posted only 1 tweet in the entire period of data collection
- A small group of users contribute to a large number of tweets
- Pattern is consistent with similar social media studies

4.2 Spatiotemporal Analysis

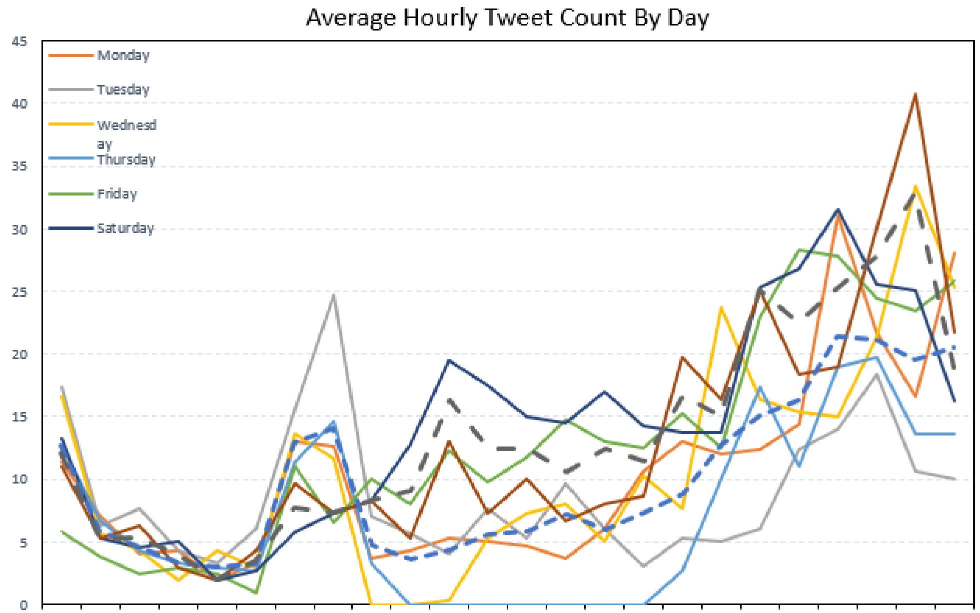
Temporal Analysis



- Daily total count of tweets in Singapore was highly variable over data collection period
- Days with lower than average tweets correspond to days with missing periods of tweet collection

4.2 Spatiotemporal Analysis

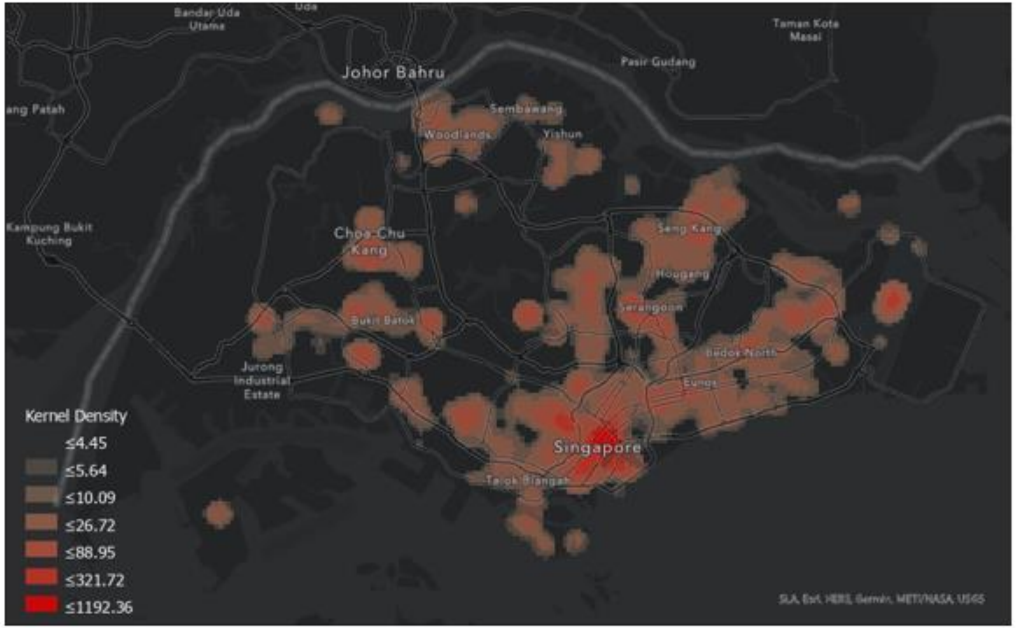
Temporal Analysis



- Weekdays: 2 peak periods
  - 6-8 AM
  - After 6PM
- Weekends: Gradual increasing tweet activity over course of day
- Fewer tweets are posted during office hours (weekday 9AM to 6PM) than other time periods

Hour of Day	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	11.33	7.00	4.00	4.33	2.00	3.33	13.00	12.67	3.67	4.33	5.33	5.00	4.67	3.67	6.00	10.67	13.00	12.00	12.33	14.33	31.00	21.67	16.67	28.00
Tuesday	17.33	6.33	7.67	4.33	3.33	6.00	15.67	24.67	7.00	5.67	4.00	7.67	5.33	9.67	6.00	3.00	5.33	5.00	6.00	12.33	14.00	18.33	10.67	10.00
Wednesday	16.67	5.67	4.33	2.00	4.33	3.00	13.67	11.67	0.00	0.00	0.33	5.33	7.33	8.00	5.00	10.33	7.67	23.67	16.33	15.33	15.00	21.33	33.33	25.33
Thursday	12.67	6.67	4.33	3.33	3.00	2.67	11.33	14.67	3.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.67	10.00	17.33	11.00	19.00	19.67	13.67	13.67
Friday	5.75	3.75	2.50	3.00	2.50	1.00	11.00	6.50	10.00	8.00	12.25	9.75	11.75	14.75	13.00	12.50	15.25	12.50	23.00	28.25	27.75	24.50	23.50	25.75
Saturday	13.25	5.25	4.50	5.00	2.00	2.75	5.75	7.25	8.25	12.75	19.50	17.50	15.00	14.50	17.00	14.25	13.75	13.75	25.25	26.75	31.50	25.50	25.00	16.25
Sunday	11.00	5.33	6.33	3.00	2.00	4.33	9.67	7.33	8.33	5.33	13.00	7.33	10.00	6.67	8.00	8.67	19.67	16.33	25.00	18.33	19.00	30.00	40.67	21.67

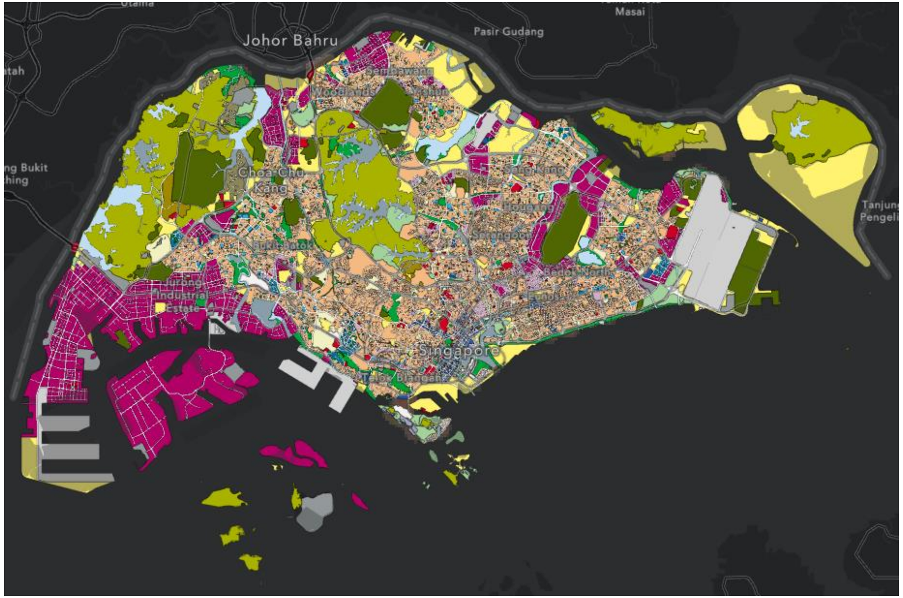
4.2 Spatiotemporal Analysis



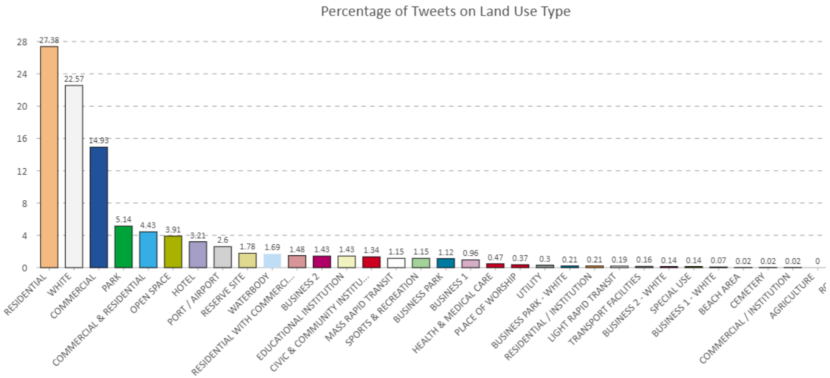
Kernel Density of tweet point features show areas with higher density of tweets (CBD, large residential estates and regional hubs)

- Incremental Spatial Autocorrelation shows peak distance at around 1km, but low z-score suggest clustering is not statistically significant
- Suggests that processes that promote global spatial clustering could be random

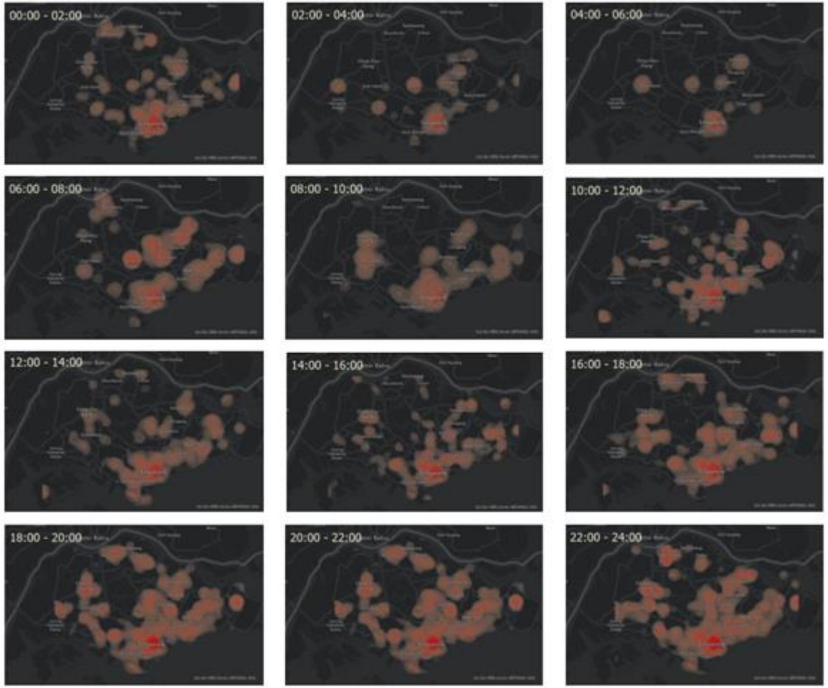
4.2 Spatiotemporal Analysis



Most tweets were posted on Residential land use (27%), followed by White and Commercial land use



4.2 Spatiotemporal Analysis



Segmenting tweets into 2-hour intervals,

- Central area presents higher density of tweets across all time periods
- 4AM to 6AM time period has the lowest spatial coverage of tweet activities, forming islands of tweet density at CBD and large residential estates
- Night time tweets cover bigger and contiguous geographical area

Conclude:

- Tweeting patterns exhibit distinct diurnal and weekly trends
- Visually distinct areas with higher density do not form statistically significant clusters suggests that high density areas are random

4.3 Ordinary Least Squares (OLS) Regression Analysis

5 out of 12 explanatory variables were removed for reflecting a high VIF value or high correlation R-Squared value.
Resulting final model has a lower VIF value for remaining variables and significance of the Koenker (BP) statistics has increased.

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	2.617869	0.977584	2.677898	0.007457*	0.515090	5.082355	0.000001*	--------
NEAR_TS	0.000327	0.001376	0.237558	0.812246	0.000311	1.050645	0.293520	5.077168
NEAR_SM	-0.000115	0.001023	-0.112840	0.910151	0.000161	-0.716291	0.473876	3.844214
NEAR_R1C	0.000402	0.000841	0.477476	0.633082	0.000292	1.375138	0.169232	3.966233
NEAR_PARKS	-0.001665	0.001040	-1.600856	0.109557	0.001037	-1.605238	0.108589	4.196250
NEAR_MRT	-0.000985	0.001275	-0.772473	0.439901	0.000967	-1.018711	0.308433	5.082725
NEAR_MF	-0.000132	0.000756	-0.174586	0.861411	0.000197	-0.671337	0.502068	4.615759
NEAR_HC	0.000095	0.001034	0.091984	0.926702	0.000152	0.625780	0.531521	5.683691
NEAR_DUS	0.000359	0.000830	0.432495	0.665437	0.000784	0.457380	0.647455	4.034707
NEAR_CC	0.001166	0.001413	0.825607	0.409097	0.000638	1.828182	0.067651	10.586366
NEAR_BUS	0.001095	0.002416	0.453044	0.650574	0.000963	1.136671	0.255788	4.423079
NEAR_SCDP	0.000030	0.000611	0.049140	0.960798	0.000112	0.266909	0.789568	3.002643
NEAR_PCN	-0.000299	0.000688	-0.435474	0.663274	0.000348	-0.859633	0.390064	2.571266

Input Features:	tweetsaggregated2	Dependent Variable:	ICOUNT
Number of Observations:	2369	Akaike's Information Criterion (AICc) [d]:	21538.410322
Multiple R-Squared [d]:	0.002627	Adjusted R-Squared [d]:	-0.002453
Joint F-Statistic [e]:	0.517121	Prob(>F), (12,2356) degrees of freedom:	0.905105
Joint Wald Statistic [e]:	31.356328	Prob(>chi-squared), (12) degrees of freedom:	0.001738*
Koenker (BP) Statistic [f]:	5.344480	Prob(>chi-squared), (12) degrees of freedom:	0.945473
Jarque-Bera Statistic [g]:	502292827.010291	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	2.177624	0.774149	2.812927	0.004953*	0.227043	9.591237	0.000000*	--------
NEAR_TS	0.000199	0.001102	0.180254	0.856961	0.000178	1.117468	0.263903	3.258452
NEAR_SM	-0.000301	0.000861	-0.349017	0.727122	0.000312	-0.962024	0.336122	2.728471
NEAR_R1C	0.000613	0.000751	0.816322	0.414385	0.000330	1.857277	0.063396	3.166298
NEAR_PARKS	-0.001257	0.000921	-1.365674	0.172183	0.000857	-1.466716	0.142601	3.293348
NEAR_DUS	0.000877	0.000621	1.412313	0.158003	0.001017	0.861559	0.389003	2.262284
NEAR_SCDP	0.000045	0.000592	0.076050	0.939369	0.000105	0.428480	0.668356	2.823583
NEAR_PCN	-0.000271	0.000647	-0.419376	0.674995	0.000375	-0.723198	0.469622	2.281214

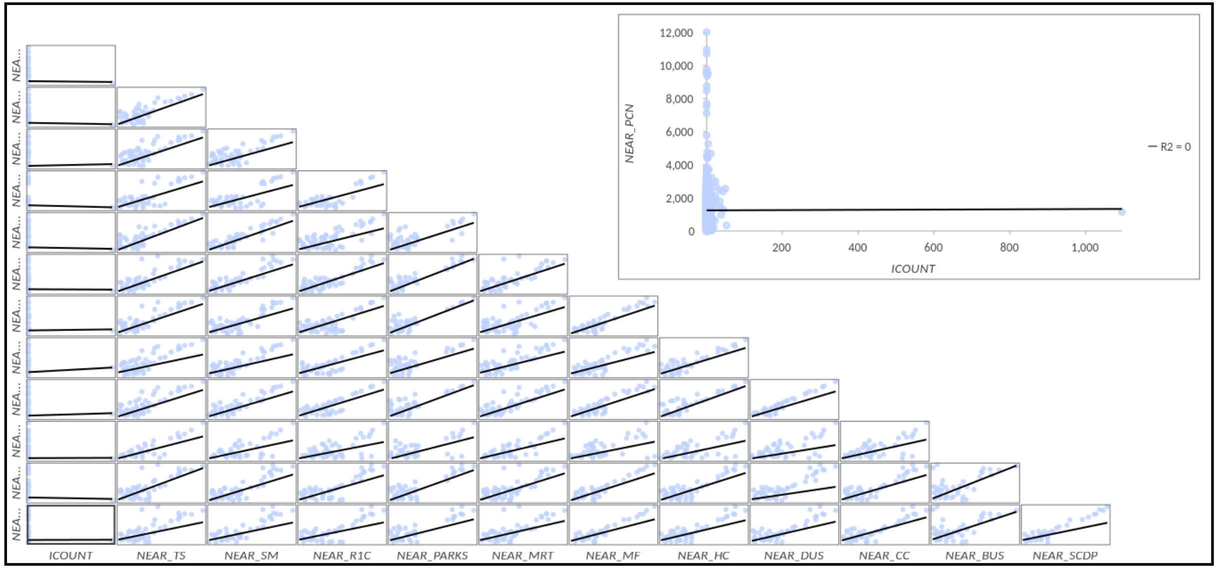
Input Features:	tweetsaggregated2	Dependent Variable:	ICOUNT
Number of Observations:	2369	Akaike's Information Criterion (AICc) [d]:	21529.788308
Multiple R-Squared [d]:	0.002004	Adjusted R-Squared [d]:	-0.000955
Joint F-Statistic [e]:	0.677156	Prob(>F), (7,2361) degrees of freedom:	0.578026
Joint Wald Statistic [e]:	17.811667	Prob(>chi-squared), (7) degrees of freedom:	0.012849*
Koenker (BP) Statistic [f]:	4.568018	Prob(>chi-squared), (7) degrees of freedom:	0.712512
Jarque-Bera Statistic [g]:	502681626.493868	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

4.3 Ordinary Least Squares (OLS) Regression Analysis

Influence of 7 remaining variables:

Ranking	Variable	Coefficient (Absolute)
1	Park (NEAR_PARKS)	0.001257
2	Dual Use Scheme (NEAR_DUS)	0.000877
3	Residential with 1st Storey Commercial (NEAR_R1C)	0.000613
4	Shopping Mall (NEAR_SM)	0.000301
5	Park Connector Network (NEAR_PCN)	0.000271
6	Taxi Stand (NEAR_TS)	0.000199
7	SCDP Park Malls Public Link (NEAR_SCDP)	0.000045

4.3 Ordinary Least Squares (OLS) Regression Analysis



The residues deviate from the line of best fit and therefore is not normally distributed.

The skewness (normally distributed = 0 vs. dataset = 47) and kurtosis (normally distributed = 3 vs. dataset = 2266) values are also far from a typical normally distributed dataset.

Non- parametric tests that are free from underlying assumptions of dataset distribution could be more suitable for this study

4.4 Random Forest Regression and Modelling

Summary of Regression Diagnostics

	Training Data	**Validation Data**
R-Square	0.868	0.507
P-Value	0.000	0.000
Standard Error	0.005	0.086

- R-squared value of validation data suggests that model is able to explain 50.7% of observed variation; small p-value (<0.025) shows that it is statistically significant
- Indicates that model may still lack key explanatory variables which will improve the performance of the model
- Uncertainty in input data due to the nature of Volunteered Geographic Information data will also affect performance and accuracy of model

4.4 Random Forest Regression and Modelling

Rank	Variable	Importance	Percentage (%)
1	PARKS	157902.84	22
2	SDCP PARK MALLS PUBLIC LINK	104611.88	14
3	TAXI STANDS	75827.32	10
4	RESIDENTIAL	72528.73	10
5	SHOPPING MALLS	54777.42	8
6	RESIDENTIAL WITH COMMERCIAL AT 1ST STOREY (Continuous, Distance Feature)	48148.46	7
7	SCHOOLS	30755.03	4
8	HOTEL	30067.48	4
9	MEDICAL FACILITIES	24600.19	3
10	MRT STATIONS	21550.71	3
11	COMMUNITY CLUBS	21163.32	3
12	PARK CONNECTORS	14511.27	2
13	HAWKER	13645.71	2
14	COMMERCIAL & RESIDENTIAL	13147.71	2
15	RESIDENTIAL WITH COMMERCIAL AT 1ST STOREY (Categorical, Landuse type)	9161.57	1
16	SPORTS & RECREATION	8389.23	1
17	COMMERCIAL	6670.87	1
18	BUS STOPS	6664.18	1
19	PLACE OF WORSHIP	4576.85	1
20	EDUCATIONAL INSTITUTION	3058.23	0

- Top 20 variables ranked according to importance in driving results of the random forest model
- Top 5 variables make up more than half of variable importance

5.0 Discussion

5.1 Spatiotemporal Tweet Patterns and Contribution from Service Amenities

- Distinct diurnal and weekly activity patterns that closely resemble typical office work temporal profile
- No statistically significant spatial cluster
- Activity patterns post-CB could <u>not</u> be adequately explained by distance to service amenities
    - OLS Regression using distances to service amenity POIs as explanatory variables
        - Results suggest poor model accuracy and absence of significant variable
        - Distance to service amenities not strong explanatory factor for activity patterns
- Random Forest Model
    - Improved model performance
    - identified amenities and land use type that were more important explanatory variables for activity patterns
- Residential land was included in random forest method but not OLS regression. With high percentage of tweets coming from residential land probably due to work-from-home arrangements

5.2 Suitability of Twitter Data for Geospatial Research on Singapore

- Twitter data rarely used to study activity patterns in Singapore
- Twitter user group is a biased representation of the Singapore resident population
  - Small number of users as compared to population
  - Uneven representation: might be more representative of young adults
  - Among Twitter users, each user is unevenly represented: majority posted 1 tweet over the data collection period
- Inconsistent quality of spatial attributes
- Data quality influenced by Tweeting habits
  - Relies on voluntarily posted tweets
- Limitations with free-of-charge public API
  - Amount of tweets collected will not exceed 1% of all tweets posted by users

⇒ Consider using chargeable Premium API to access the full Twitter dataset
⇒ Scope targeted research questions that can be adequately answered with Twitter data

5.3 Other Limitations

1. Absence of Pre-CB Activity Pattern as a Benchmark
   - Prevents a comparison of pre- and post-CB activity patterns in order to assess the effectiveness of safe distancing and risk communication measures on physical activity patterns
2. Missing Time Periods in Data Collection
   - Limits accurate understanding of temporal tweet patterns
3. Geocoding
   - Data collected in Place_Name field often invalid (improper place names, spelling mistakes, etc) -- result in unsuccessful conversion and therefore excluded from geocoding process
   - Place names with general location (e.g. Central Region) rather than specific location -- results in inaccurate location
   - Place names that may occur in more than one location (e.g. Fairprice) -- may results in inaccurate location

6.0 Conclusion

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What we have presented:

- An attempt to explore spatiotemporal activity patterns in Singapore after Circuit Breaker using Twitter data
- A discussion of how Twitter data may be relevant for geospatial research in Singapore
- Preliminary insights to whether service amenities and land uses might impact (or not) spatial activity patterns in post-CB Singapore

Recommendations for further research:

- Long-term monitoring of activity patterns to understand behaviour changes, and effectiveness of regulations
- Twitter data is still valuable; appropriate research questions can be scoped bearing in mind the inherent limitations of such VGI data

7.0 References

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