Spatiotemporal Population Movement for Ground Risk of Unmanned Aerial Vehicles (UAVs) in Urbanized Environments using Public Transportation Data

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Unmanned aerial vehicles (UAV) or 'drones' are expected to increase in the future and be employed for a multitude of applications like parcel delivery, industrial inspection, aerial photography, and safety surveillance. Consequently, increase in UAV traffic may lead to higher likelihood of UAV failure and crash to occur. For urbanized environments, operation of UAV poses high risk to the population on ground due to increased population movement and expectation of people to be outdoors. Diffusive model simulation using random walk was employed to estimate population movement outside buildings at different times especially near Mass Rapid Transit (MRT) train stations. In our preliminary study, the influence of different times to the population movement was highlighted. It was observed that the population was more concentrated around MRT stations at morning and afternoon during weekdays, while more constant throughout the day during weekends or holidays. Ground risk mapping due to UAV operation could also be studied and performed in future study to have better understanding on this risk. Study of population movement in urbanized environments for the ground risk assessment of UAV operations will provide better insights on the limitation of current risk assessment. At the same time, this could help provide information for national aviation authorities to formulate risk assessment and approve UAV operation in urban environments.

I. Introduction

Unmanned Aerial Vehicles (UAV), commonly referred to as 'drones', have piqued the public's curiosity in the last decade. Emergence of the UAV industry is attributed to its potential for operation in a multitude of applications such as aerial photography, parcel delivery, and building inspections. Forecasts predict that the global UAV market is projected to grow to USD 90 billion by year 2030, a swift increase from USD 15 billion in 2020 [1].

Consequently, increase in UAV traffic in the future may lead to a higher likelihood of UAV failure and crash to occur. Since UAV do not have passengers on board the vehicle, the threat will be mainly to persons and properties on the ground as well as upon other airspace users [2]. This is frequently referred to as Third-Party Risk (TPR) which includes Ground Risk and Air Risk. For urbanized environments, operation of UAV poses high risk to the population on ground due to increased population movement and expectation of people to be outdoors [3]. This highlights the need to study the ground population movement in urbanized environments.

The Joint Authorities for Rulemaking of Unmanned Systems (JARUS) defined the probability of a third-party ground fatality due to an unmanned aircraft (UA) hazard to be a function which encompasses the accident rate, population density, and the dynamics of impact [4]. Hence, several studies have incorporated the population density parameter that is exposed to the UAV operation in their risk model [5–7]. Investigating spatiotemporal population methods are a continuing concern and there is a lack of consensus as to which model to adopt for UAV ground risk analysis.

The aim of this study was to investigate the spatiotemporal behavior of the population in urbanized environments by employing diffusive model simulations using random walk near Mass Rapid Transit (MRT) train and Bus stations.

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Understanding of the temporal behavior of the population in urbanized environments is imperative for the deployment of UAV operations as temporal population information requires to be analyzed and its models should be incorporated in ground risk assessments. Study of population movement in urbanized environments for the ground risk assessment of UAV operations will provide better insights on the limitation of current risk assessment. At the same time, this could help provide information for national aviation authorities to formulate risk assessment and approve UAV operation in urban environments.

The literature is structured as follows, review of prior and relevant literature in this field of study is presented in Section II. Section III elucidates the framework, methodology, and analysis used for developing the population model in this study. The densely populated and urbanized city of Singapore was selected as case study. Finally, Section IV sums up the findings, conclusions, and recommendations for future research.

II. Literature Review

In this section, relevant work that have been influential in this field of study will be reviewed. It was examined that majority of people will spend a fraction of their daily time to be outdoors, either for going to workplace, schools, recreational activities, or shopping. Study by Melnyk et al. [8] showed people spent around 7.6% of their total time to be outdoors in the United States. Figure 1 illustrates the percentages that were used by [8]. This percentage was determined based on the survey and analysis of population movement and behavior in various settings by the United States Environmental Protection Agency [9], seen in Table 1. While the survey was conducted with the objective of determining population exposure to pollutants, it is useful in providing an estimation of population frequenting at various locations. Similarly, another study by Blom et al. [10] estimated that people in Netherland spent approximately 10% of their time to be outdoors, the percentage was higher due to increased usage of bicycles and scooters by the people in Delft. Percentages that represent an increased time of people outdoors have significantly higher exposure to the risk of being hit by UAV that crash in that area.

Table 1 Population Behaviour in United States [9]

Information	Percentage
Time spent in Residence	68.7 %
Time spent Outdoors	7.6 %
Time spent in Vehicle	5.5 %
Time spent in Office	5.4 %
Time spent Indoors	12.8 %

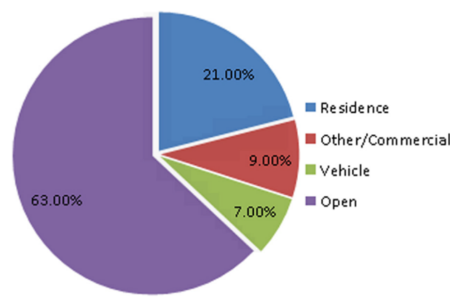


Fig. 1 Breakdown of Ground Area [8]

In urbanized countries such as Singapore where population density is considerably higher. Movement of population is achieved mostly by their efficient transportation system, e.g., Mass Rapid Transit (MRT) and Light Rail Transit (LRT) trains, buses, taxi, and e-hailing. A survey conducted by the Singapore Department of Statistics on the Census of Population in 2020 [11] showed that public transportation modes of MRT and buses were the most significant mode of transportation preferred by residents. It was specified that in 2020, 57.7% of employed residents travelled by MRT/LRT, public bus, or combinations of MRT/LRT or public bus to their workplace. The percentage of modes of transportation by the population in Singapore is illustrated in Fig. 2. Consequently, frequent usage of MRT by commuters suggest that more people will be concentrated near the vicinity of MRT stations and bus stops at different times throughout the day [11]. For instance, more people are expected to be around MRT stations in the morning as people are rushing to their workplace while less people are anticipated in the afternoon as people stay at home or at the workplace.

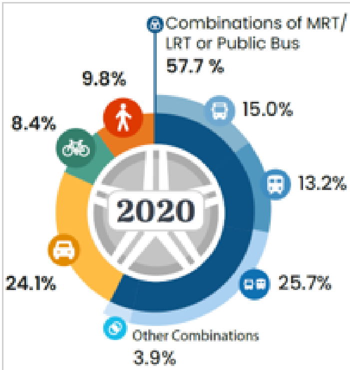


Fig. 2 Modes of Transport by Employed Residents [11]

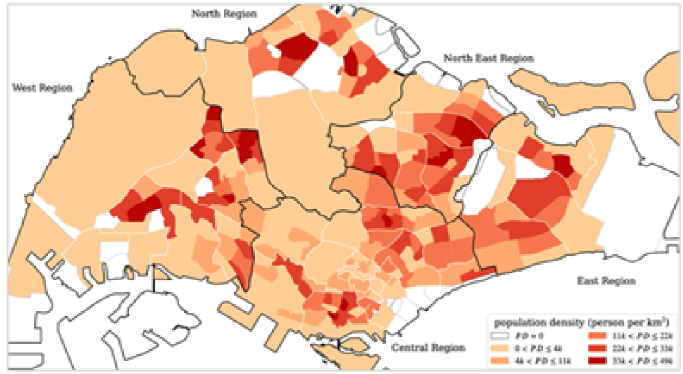


Fig. 3 Subzone Residential Population Density of Singapore based on Census information [12]

Several researchers have employed risk mapping to visualize ground risk from UAV operations in urbanized environments [13–15]. Risk mapping is essential in illustrating the critical areas that require an increase in UAV reliability for operation. Commonly, risk mapping of the population exposed is performed with the use of spatial population data from census. However, implementation of census spatial population data directly in the modelling of population provides an inadequate estimation of ground risk as people are constantly on the move especially within densely populated areas and urbanized environments. This limitation is observed in Fig. 3 where the residential population density is static and spatially aggregated [12]. On the contrary, some literatures extract call detail record (CDR) or mobile phone data to analyze mobility patterns and estimate the number of people at urbanized areas [16, 17]. However, this technique requires retrieving data from telecommunications providers which are usually not publicly available.

The use of smart cards in public transportation has been pivotal in recording and gathering big data for population mobility analysis. For instance, Holleczek et al. studied urban mobility patterns and choices of transportation modes with the use of datasets comprising of mobile phone CDR information and a public transport smart card dataset [18]. Ridership on public transportation by commuters is captured effectively by these smart cards and available minimally as open-source data. Hence, this study incorporated open-sourced transportation data such as MRT and Bus ridership.

III. Methodology for Estimating Population Movement

To estimate the population density around MRT stations for ground risk, a series of diffusive models using random walks were employed. The workflow of study is illustrated in Figure 4. An outline of the population movement simulation methodology is described as follows:

1. Firstly, data acquisition and analysis of open-source transportation data of MRT and Bus ridership from Land Transport Authority (LTA) DataMall. This is performed to identify stations with increased human traffic.

2. Secondly, perform diffusive model simulation using Random Walk (Python) to estimate population movement at different times for highly traveled MRT and Bus stations in subzone regions of interest.

3. Lastly, conclusions will be drawn from the results by comparing population movement at different times and the associated risk map.

A. Data Acquisition and Processing

The primary datasets adopted in this study include the open-sourced transportation data from LTA DataMall. LTA DataMall provides a great variety of static and dynamic datasets of commuters travelling on public transportation. The dataset on passenger volume by MRT train stations was queried through the DataMall API [19]. The query returned the hourly tap in and tap out of passengers for individual MRT train stations based on weekday and weekend for the month of September 2021. For this dataset, passenger tap in refers to commuters entering the MRT train station with their smart card while passenger tap out refers to commuters exiting after travel. This behavior is illustrated in Fig. 5 in which the left most passengers are tapping out and exiting the MRT train station. In addition, Table 2 shows the top 5 MRT stations with the highest total passenger tap out registered and its respective time of day.

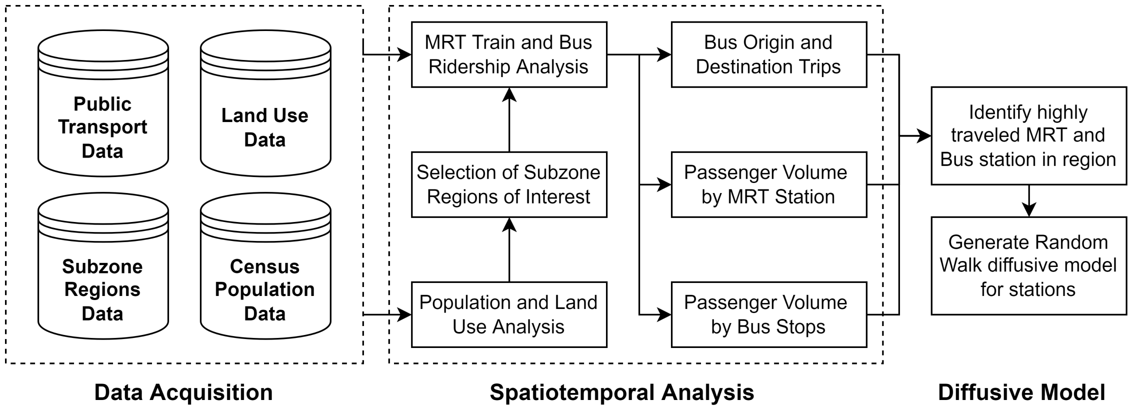


Fig. 4 Workflow of Study

Table 2 Top 5 Highest MRT Stations (Monthly Tap Out)

Day Type	Destination MRT Station	Tap Out	Time of Day
Weekday	Jurong East	126,136	07:00 - 07:59 am
Weekday	Yishun	113,562	18:00 - 18:59 pm
Weekday	Joo Koon	98,638	07:00 - 07:59 am
Weekday	Jurong East	96,741	08:00 - 08:59 am
Weekday	Woodlands	96,481	18:00 - 18:59 pm

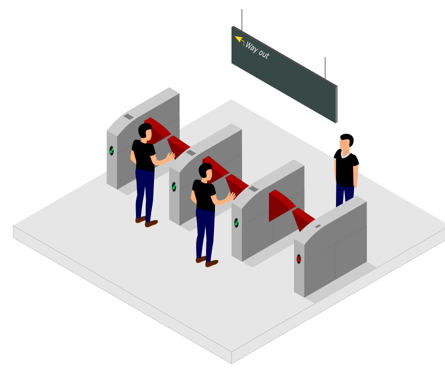


Fig. 5 Breakdown of Ground Area [8]

Similarly, datasets on passenger volume and origin-destination (OD) trips by bus stops were queried through the DataMall API [19]. The first query returned the hourly tap in and tap out of passengers for individual bus stops based on weekday and weekend for the month of September 2021. Likewise, the second query returned the hourly trips of passengers from origin to destination bus stops. Information of OD trips by bus provides useful insights on travel patterns of commuters to neighboring regions. Additionally, land use data of the Singapore region for the year of 2014 [20] was acquired to analyze the distribution of building types within regions, illustrated in Fig. 6. The land use data extracted was grouped into categories adapted from [21, 22]. Analysis of the land use data and classifications facilitated the selection of subzone regions of interest, addressed in Section IV.

MRT rail network and bus coverage within Singapore, illustrated in Fig. 7, explains the wide usage of public transportation modes, as examined by [11]. The vast coverage of the MRT and bus stations provides great accessibility for people of all ages due to its proximity to residences and businesses. Hence, public transportation analysis would provide a reasonable approximation of inflow and outflow of passengers within subzone regions critical for spatiotemporal population modeling.

Correspondingly, Popular times data from Google Maps was extracted for these individual MRT stations with the use of Live Popular Times library compatible for Python [23]. An external library for web scraping had to be utilized as this data is currently inaccessible through the Google Maps API. The popular times data provided the average frequency and popularity that passengers are present in the location for days of the week over the past few months. Google states that this anonymized data is recorded by users that activate their Location History. Hence, this data was analyzed with the caveat that the frequency might not be available for all MRT train stations. It is noteworthy that Popular times data was extracted only for comparison with the DataMall transportation data and was not used in the population modelling. A summary of the datasets acquired for analysis is presented in Table 3.

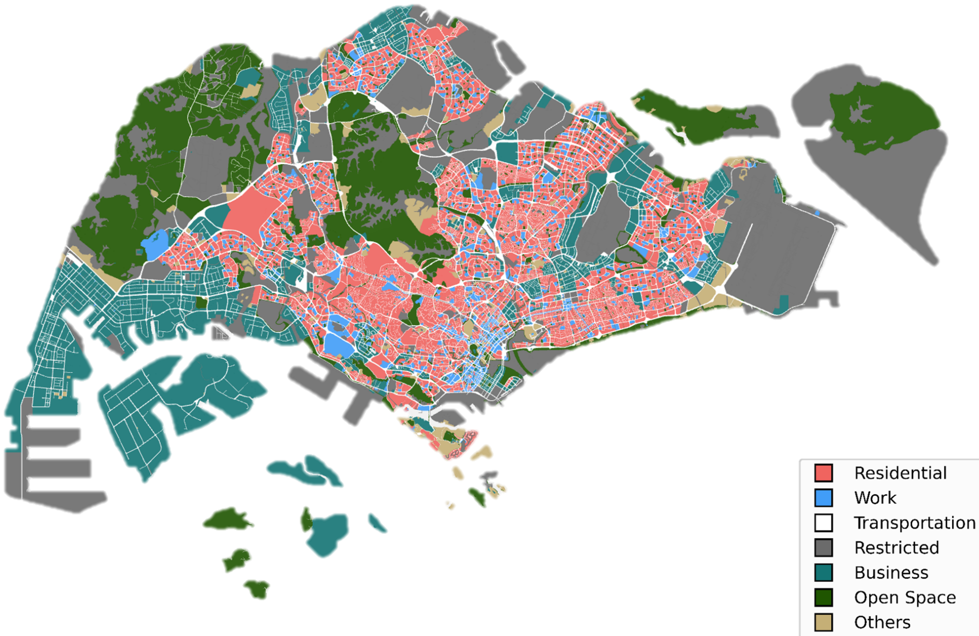
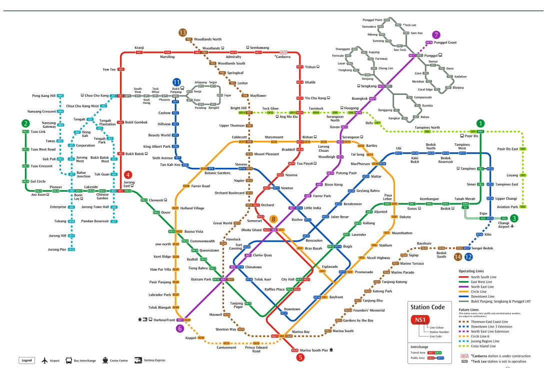
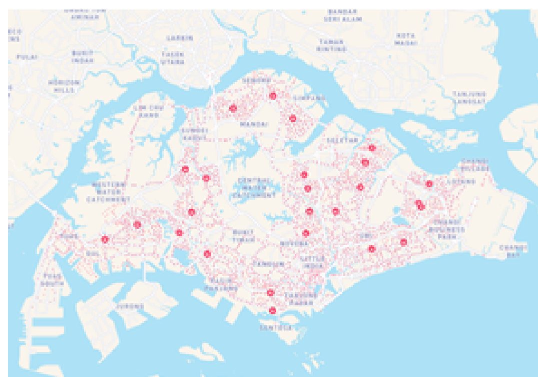


Fig. 6 Land Use Classification for Singapore Subzone Regions (Generated with Kepler.gl v2.5.5 using Master Plan 2014 Land Use Dataset [20] and classifications adapted from [21, 22]



(a) MRT Rail Network in Singapore [24]



(b) Public Bus Coverage in Singapore [25]

Fig. 7 Network and Coverage of MRT Rail and Public Bus (Figures adapted from [24, 25]

Table 3 Summary of Open-Sourced Datasets Considered in Study

Name of Dataset	Description	Source (Year)	Purpose of Data
Passenger Volume by Train Stations	Hourly tap in and tap out of passengers for individual MRT train stations.	LTA DataMall (2021) [19]	Analysis of passengers commute at MRT train stations.
Passenger Volume by Bus Stops	Hourly tap in and tap out of passengers for individual bus stops.	LTA DataMall (2021) [19]	Analysis of passengers commute at Bus stops.
Passenger Volume by Origin Destination Bus Stops	Hourly trips of passengers from origin to destination bus stops.	LTA DataMall (2021) [19]	Analysis of travel patterns of commuters to neighboring regions.
Bus Stops Information	Detailed information of all bus stops, such as bus stop code and location coordinates.	LTA DataMall (2021) [19]	Visualization of geospatial data for bus stop location.
Master Plan 2014 Land Use	Indicative polygon of each development land parcel (residential, commercial areas)	Data.gov.sg (2014) [20]	Distribution of residential and commercial buildings in region of interest.
Master Plan 2014 Subzone Boundary	Indicative polygon of subzone boundary (regions of interest)	Data.gov.sg (2014) [26]	Visualization of geospatial data of Singapore regions.
Popular Times	Hourly frequency of population presence in area of interest.	Google Maps (2022) [23]	Comparison with DataMall transportation data

B. Simulation of Population Movement

Since the objective of this study was to investigate the spatial and temporal behavior of the population in urbanized environments, random walk / brownian motion simulations were performed. For these simulations, the total quantity of passengers tap out from MRT stations and bus stops was utilized. This will be used as the number of walkers in the simulation. Additionally, results are generated for the maximum case within time intervals of 6am-8am, 9am-3pm, 4pm-8pm, and 9pm-12am. For instance, it was observed that 126,136 passengers tapped out from Jurong East MRT station at 7am on a typical weekday. This was also the maximum case within the 6am-8am time interval. Hence, this will be the equivalent value to be used in the simulation.

Two-dimensional random walk simulations were generated using the RandomWalk class from the pytrax library [27], which is written in Python. Inputs required in the simulation comprise of the number of walkers that will run concurrently, total number of steps each walker takes, and whether walkers all start from the same origin. The random walk algorithm used in pytrax library does not constrain walkers to their 2D domain boundaries by adopting an array of domains that are real and reflected and treating the domain as a representation of a larger medium [27]. The total number of steps each walker takes was assigned to be 1000 for all simulations. This was performed to illustrate the distribution of passengers diffusing from the MRT station while minimizing computational cost. It is notable that walkers and their positions follow a Gaussian distribution that spreads outwards in this simulation. Codling et al. states in his study of random walk models for biology that spatial coordinates of walkers on any axis converges to a Gaussian distribution (G) once a certain amount of time has elapsed [28]. The probability density function (PDF) for an individual walker's location after elaped time t and diffusivity D is given by [29].

$$G(x, t|D) = \frac{1}{\sqrt{4\pi D t}} \exp \frac{-x^2}{4Dt} \tag{1}$$

IV. Data Analysis and Results Discussion

In this section, results generated from the temporal data analysis and simulation will be presented on four subzone regions. Subzone regions of interest that were selected for study include Jurong Gateway, Jurong West Central, Choa Chu Kang Central, and Joo Koon, shown in Fig. 8. Jurong West Central also has the highest population density of 45,396/km^2 in Singapore. Hence, western subzone regions near this area were focused on. It is notable that the regions of Jurong Gateway (811.4/km^2) and Joo Koon (12.77/km^2) were commercial and industrial areas respectively. Jurong West Central and Choa Chu Kang Central (20,562/km^2) were highly residential areas. Figure 8 displays regions colored based on static census population density in Red, Yellow, Green color scheme with green denoting low residential population while red refers to high residential population. Regions were specifically chosen based on the criteria that they include both a MRT train station and bus interchange. Bus interchanges are equivalent to bus terminals where multiple bus services are handled with connections to the MRT train network. This characteristic will facilitate in investigating the quantity of commuters using transportation data for MRT train stations and bus stops. It is noteworthy that these regions are also differentiated based on their distinctive land use classification and variation in static population density.

A. Land Use Analysis

The subzone regions of interest were analyzed for their distribution of building types using the Master Plan 2014 land use data, illustrated in Fig. 9. Jurong Gateway region was observed to have a large majority of buildings that are associated to business and work categories. Similarly, almost all buildings in the Joo Koon region are associated to the business category. This is clearly understood as the Joo Koon region is an industrial estate and explains the low residential population captured in census static population density.

In contrast, regions of Jurong West Central and Choa Chu Kang Central have a large majority of residential buildings with a few buildings associated with the work category. These buildings associated to work are expected to be educational institutes or schools which are more common in residential regions. Hence, this explains the high residential population captured in census static population density. However, static population density from census data is inadequate in accurately modelling the ground risk posed due to UAV operation. The spatially aggregated and static population data from census assumes uniformity within region and fails to capture dynamic and temporal variations. Hence, temporal analysis using public transportation will be beneficial in approximating the population movement within regions.

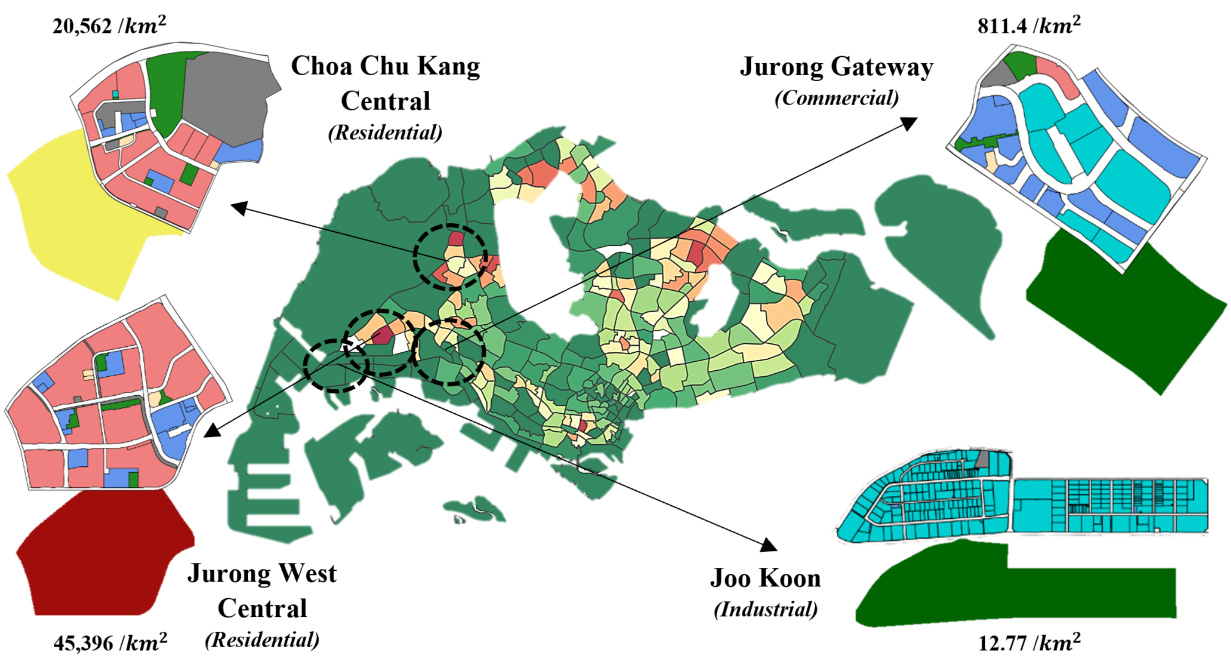


Fig. 8 Selection of Subzone Regions of Interest with Population Density in Background

B. Transportation Data Analysis

Passenger volume for train stations and bus stops within the four individual subzone regions were analyzed at hourly intervals. The total tap in volume and tap out volume is illustrated in Fig. 10. For bus stops, the bus interchange and next commonly used bus stop is displayed. It was deduced that Boon Lay MRT station (situated in Jurong West Central) and Choa Chu Kang MRT stations indicate equivalent inflow and outflow of passengers as they are in residential regions. Heavy passenger volumes are expected at 7am and 7pm in these regions. Additionally, Jurong East MRT station (situated in Jurong Gateway) and Joo Koon MRT station share a similar pattern where the quantity of passenger tap out is greater in the morning. Conversely, the quantity of passenger tap in is greater in the evening for these two regions. This is expected as commuters tap out from these MRT stations in the early morning to head to work in these regions and tap in again in the evening to head back to their residence.

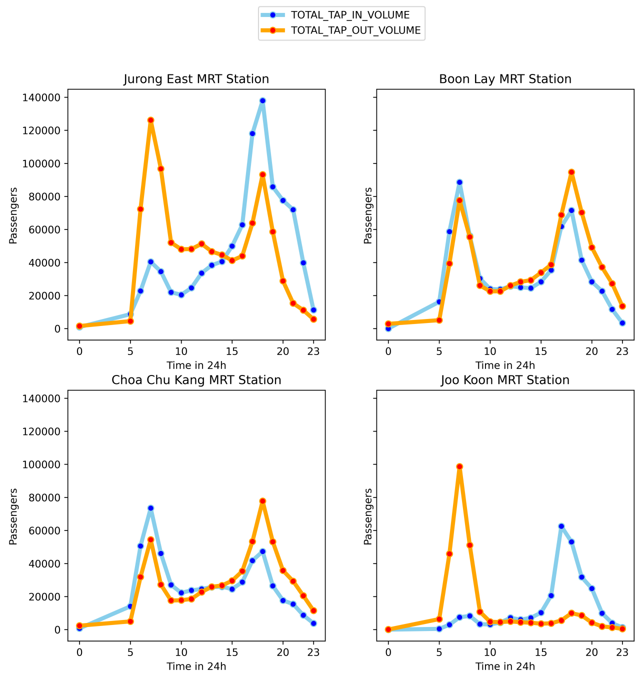
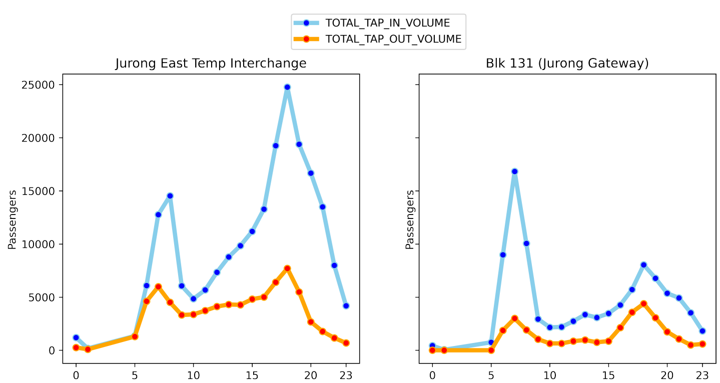
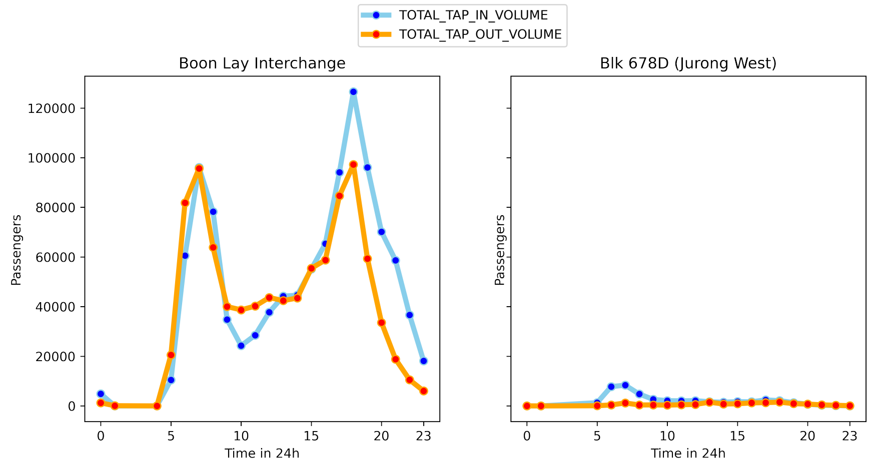


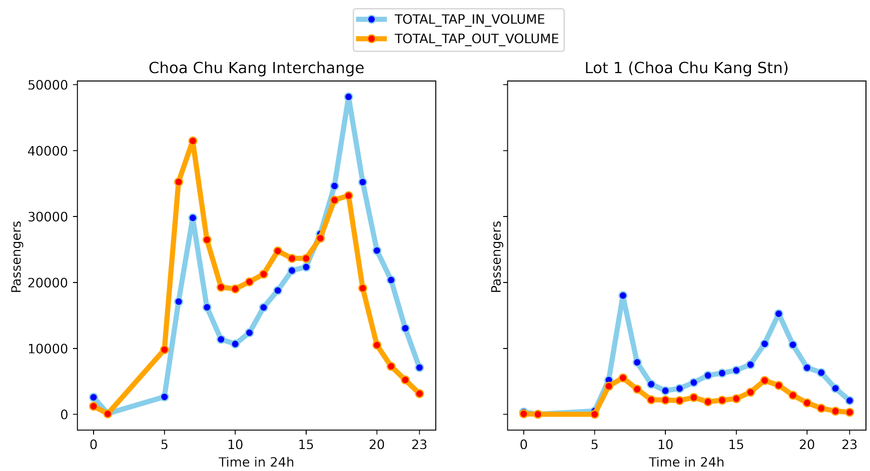
Fig. 9 Hourly Passenger Volume by MRT Stations in Subzone Regions



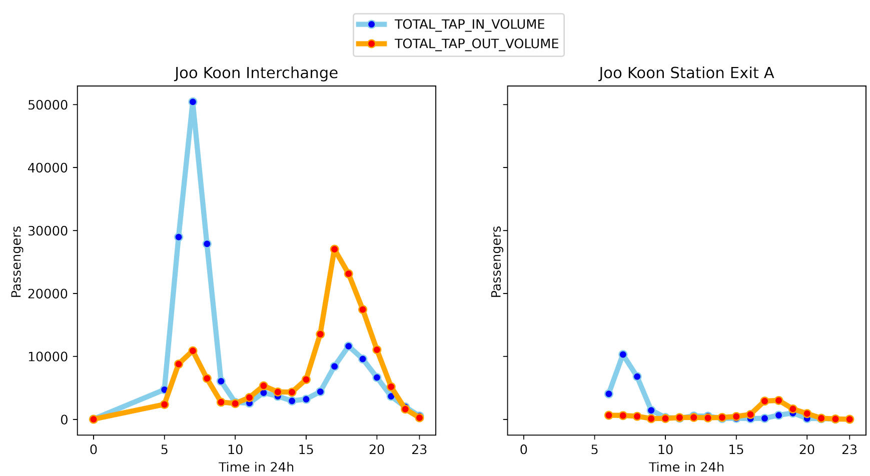
(a) Interchange and Bus Stop closest to MRT Station (Jurong Gateway)



(b) Interchange and Bus Stop closest to MRT Station (Jurong West Central)



(c) Interchange and Bus Stop closest to MRT Station (Choa Chu Kang Central)

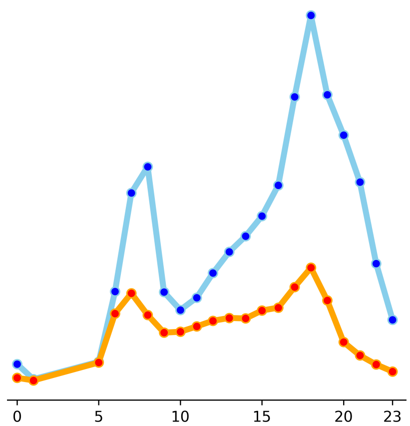


(d) Interchange and Bus Stop closest to MRT Station (Joo Koon)

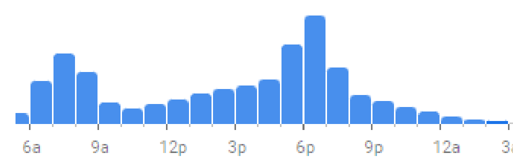
Fig. 10 Hourly Passenger Volume by Bus Stops in Subzone Regions

Similarly, the hourly passenger volume by bus stops for interchanges in Jurong Gateway, Jurong West Central, and Choa Chu Kang were observed to have a similar temporal pattern. In Fig. 11, for interchanges in residential regions such as b) and c), there are two distinct peaks which are at close to 7am and 6pm. This indicates frequent passenger tap out in the early morning and frequent passenger tap in in the evening. Furthermore, there is relatively low passenger volume for all cases close to 10am. This would likely indicate a lower risk for UAV operations as there would be lesser commuters to be overflown.

Popular times data extracted from Google Maps was used to verify the temporal trends for the transportation data in subzones of interest. As an example, the comparison is shown for Jurong Gateway region in Fig. 12. It was observed that the highest peaks appear to match. However, it is noteworthy that transportation data captures both passengers tap in and tap out. This facilitates the modelling of passenger inflow and outflow in population models. In contrast, Google Popular Times captures only the population present in the area based on their access to location services.



(a) MRT Train Data



(b) Google Popular Times Data

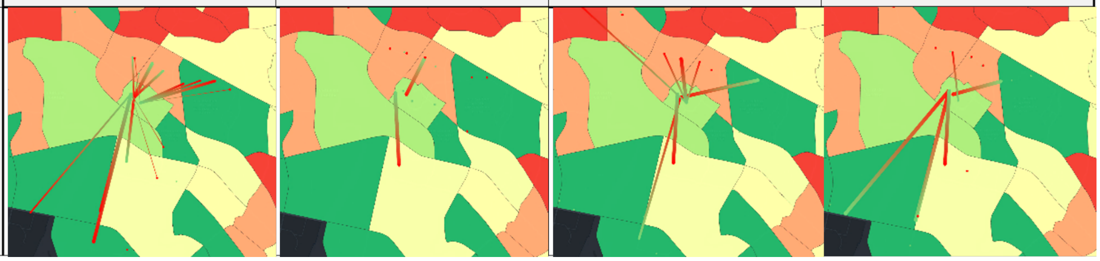
Fig. 11 Comparison of Transportation Data with Google Popular Times in Jurong Gateway

C. Risk Mapping of Passenger Origin-Destination Bus Trips

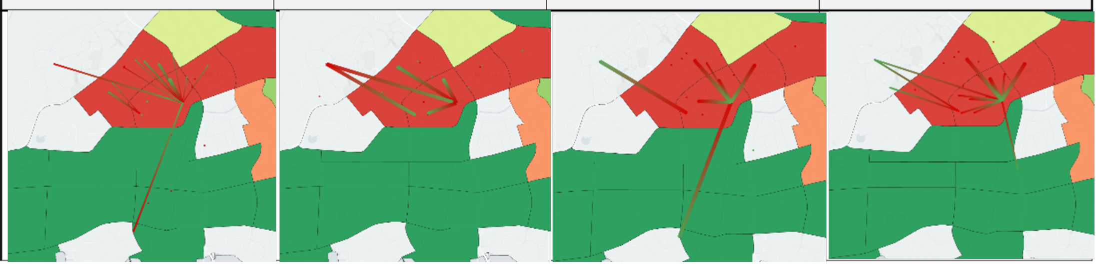
Spatiotemporal movement and patterns of commuters were mapped in the subzone region of interest using MRT and Bus ridership data. It can be expected that commuters patronize multiple combinations of public transportation modes within a region. For instance, commuters tap out from MRT station and take a public bus to their region of residence. In this study, risk mapping for UAVs was generated solely based on spatiotemporal population movement from public transportation data. Ground risk analysis for UAVs encompasses other factors such as aircraft failure rate, probable crash area, shelter factor, and fatality of human. However, these factors were not integrated in the risk map and beyond the scope of this study.

Bus OD trips approximately indicated the regions of interest, neighboring regions, and their respective bus stops which passengers patronize. This is illustrated in Fig. 13 where regions of interest are shown alongside their neighboring regions. It is notable that bus trips are computed for all timings, however, the most frequent trips within time intervals are displayed in Fig. 13. The OD trip lines are color differentiated based on origin (green) or destination (red). For each region, OD trips were analyzed both ways (i.e., to and from subzone region of interest).

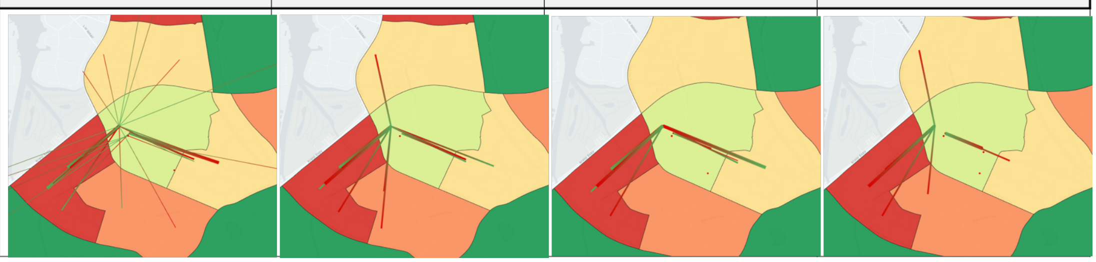
Analysis of OD bus trips highlighted that commuters frequently travel to and from neighboring regions to bus stops nearest to MRT train stations. This is especially seen in peak hours in the early morning and evening. This is observed in Fig. 13(a) where there is high movement between neighboring regions in the north. Commuters that leave their residence in the regions in the early morning are likely to return in the evening. This pattern was also captured in Fig. 13(a). Similarly, frequent bus trips for other regions of interest are illustrated in Fig. 13.

	Time Intervals (Jurong East)			
Population Model	6am-8am	9am-3pm	4pm-8pm	9pm-12am
Spatial - Temporal				

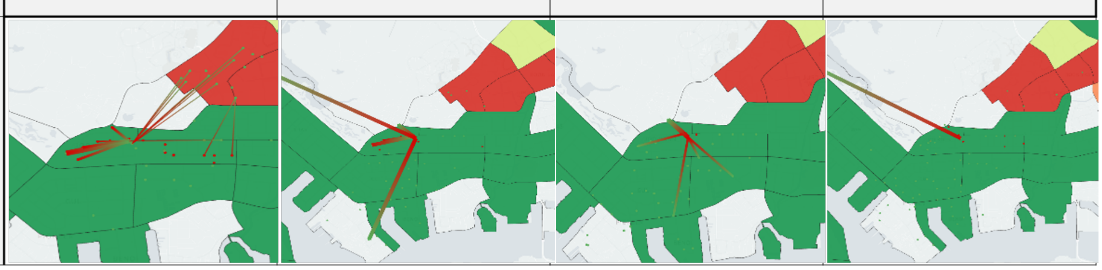
(a) Frequent Bus trips in Jurong Gateway (Jurong East)

	Time Intervals (Jurong West Central)			
Population Model	6am-8am	9am-3pm	4pm-8pm	9pm-12am
Spatial - Temporal				

(b) Frequent Bus Trips in Jurong West Central region (Boon Lay)

	Time Intervals (Choa Chu Kang Central)			
Population Model	6am-8am	9am-3pm	4pm-8pm	9pm-12am
Spatial - Temporal				

(c) Frequent Bus Trips in Choa Chu Kang Central region

	Time Intervals (Joo Koon)			
Population Model	6am-8am	9am-3pm	4pm-8pm	9pm-12am
Spatial - Temporal				

(d) Frequent Bus Trips in Joo Koon region

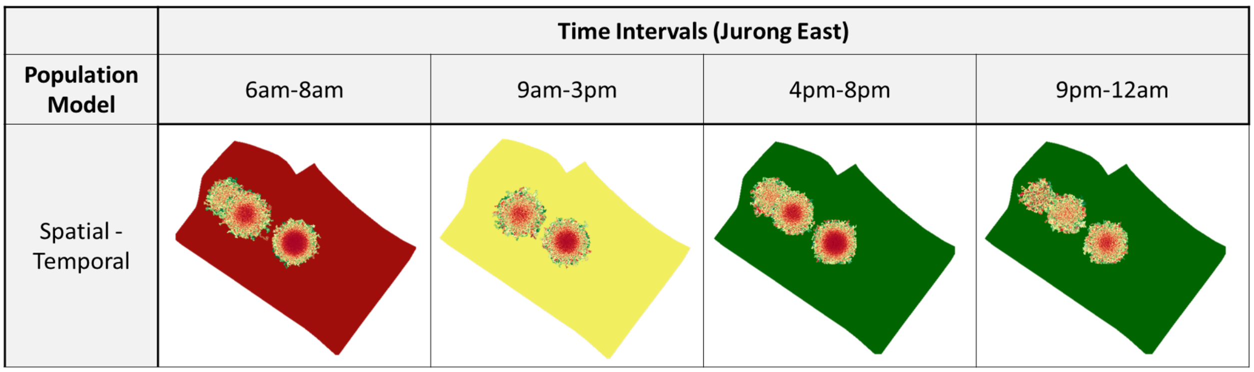
Fig. 12 Risk Map of Passenger Trips by Bus (Superimposed onto Static Census Population)

D. Spatiotemporal Mapping of Passenger Diffusion

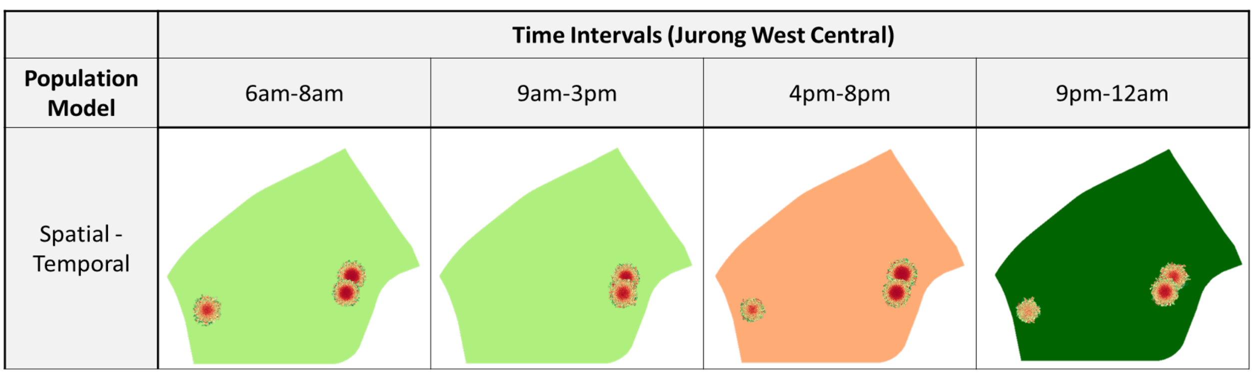
Passenger diffusion using random walk simulations was generated at highly frequented MRT stations and bus stops within subzone regions of interest. Highly frequented bus stops were identified using passenger OD trips by bus. This was to isolate and focus on bus stops with a larger majority of passengers. From these simulations, spatiotemporal mapping was performed to visually observe hotspots where increased passenger volume is likely expected. Additionally, these areas will be identified as high risk for UAV operations due to greater population movement.

Spatiotemporal population was illustrated for regions using passenger inflow and outflow. This was performed by assuming that population in the subzone region is primarily from the net amount of people, considering passenger tap in and tap out volumes. As a result, population was estimated based on public transportation for regions and computed using Eq. (2). However, this approach might only approximate the population as residential population and customers in shopping centers amongst other factors were excluded from the computation. Results for subzone regions of interest are displayed in Fig. 14.

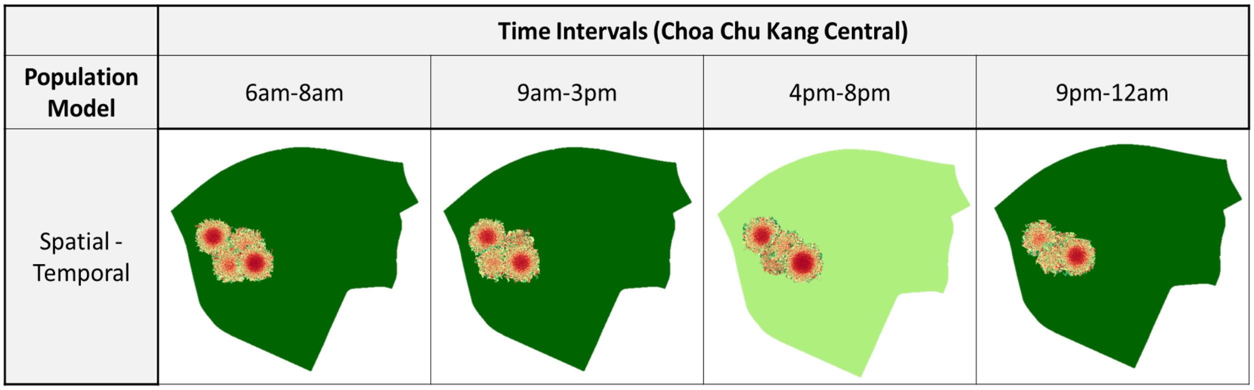
$$Pop_{net} = \sum_{i=m}^{M} MRT_{tap,out} + \sum_{i=n}^{N} Bus_{tap,out} - \sum_{i=m}^{M} MRT_{tap,in} - \sum_{i=n}^{N} Bus_{tap,in} \tag{2}$$



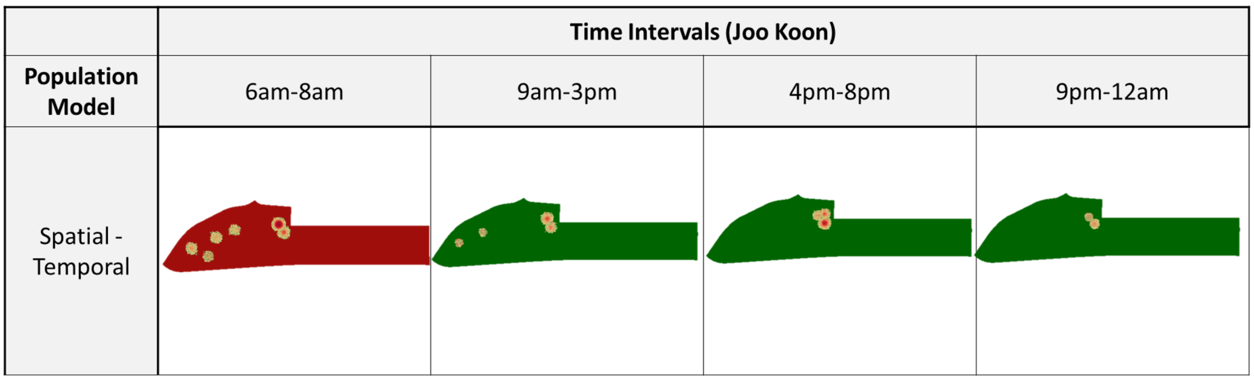
(a) Passenger Diffusion in Jurong Gateway region (Jurong East)



(b) Passenger Diffusion in Jurong West Central region (Boon Lay)



(c) Passenger Diffusion in Choa Chu Kang Central region



(d) Passenger Diffusion in Joo Koon region

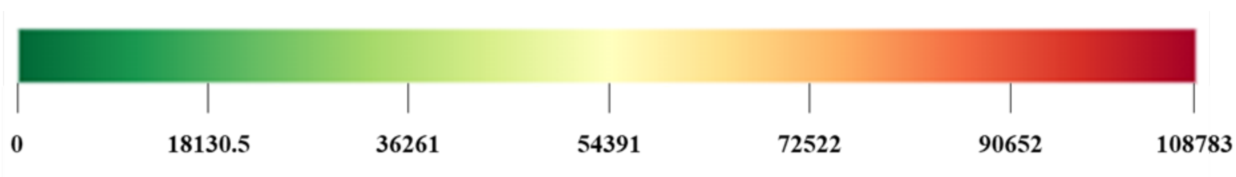


Fig. 13 Spatiotemporal Mapping of Passenger Diffusion near MRT and Bus Stations (Superimposed with Net Population Volume, Pop_{net})

V. Conclusion and Future Works

This study discussed the spatiotemporal behavior of the population in urbanized environments by employing diffusive model simulations using random walk near Mass Rapid Transit (MRT) train and Bus stations. The urbanized city of Singapore was chosen as a case study due to its highly dense population and increased accessibility to public transportation. Four different subzone regions were selected based on their variation in population density and land use type. Based on the transportation and land use data analysis, highly frequented stations were identified. Subsequently, diffusion model simulations with random walk were generated at these locations within subzone regions of interest. This was beneficial in identifying hotspots where passenger volume is likely to be greater at certain times of the day. Passenger volume at MRT stations and bus stops were also utilized to compute the net quantity of population within the region. Net population based on transportation data estimated the people within the region at a given time. However, it is noteworthy that this approach might only approximate the population as factors such as residential population and customers in shopping centers are excluded.

It was deduced that MRT stations near residential areas indicate equivalent inflow and outflow of passengers. Heavy passenger volumes are expected at 7am and 7pm in these regions. Additionally, Jurong East MRT station (situated in Jurong Gateway) and Joo Koon MRT station share a similar pattern where the quantity of passenger tap out is greater in the morning. Conversely, the quantity of passenger tap in is greater in the evening for these two regions. Commuters were observed to frequently travel to and from neighboring regions to bus stops nearest to MRT train stations. This is especially seen in peak hours in the early morning and evening. Origin-Destination (OD) trips by bus highlight generally low usage in the early afternoon and late night. This is observed especially for non-residential subzone regions. Additionally, passenger diffusion and net population was beneficial in approximating the population remaining within subzone region. Results indicated high net population in the morning for non-residential areas while net population was generally low for all regions in the late-night hours.

This study is a preliminary work to approximate the spatiotemporal behavior of population using public transportation data. Open-source public transportation data is a decent substitute to CDR data in approximating the population in regions with high transport usage and in cases where CDR data is unavailable. Several assumptions were taken in this study such as computation of net population based on passenger volume by MRT and Buses. However, further analysis with ancillary data such as educational institutes, shopping centers, and hawkers will be explored in the future for a comprehensive assessment.

In addition, other techniques for spatiotemporal population analysis [30] and its integration with UAV third-party ground risk models [31] can be studied. Study of spatiotemporal population movement in urbanized environments for third-party ground risk assessment of UAV operations will provide better insights on the limitation of current risk assessment. At the same time, this could help provide accurate information for aviation authorities to formulate risk assessment and approve UAV operation in urban environments.

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