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Using Building Floor Space for Station Area Population and Employment Estimation

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Abstract: Analyzing population and employment sizes at the local finer geographic scale of transit station areas offers valuable insights for cities in terms of developing better decision-making skills to support transit-oriented development. Commonly, the station area population and employment have been derived from census tract or even block data. Unfortunately, such detailed census data are hardly available and difficult to access in cities of developing countries. To address this problem, this paper explores an alternative technique in remote estimation of population and employment by using building floor space derived from an official administrative geographic information system (GIS) dataset. Based on the assumption that building floor space is a proxy to a number of residents and workers, we investigate to what extent they can be used for estimating the station area population and employment. To assess the model, we employ five station areas with heterogeneous environments in Tokyo as our empirical case study. The estimated population and employment are validated with the actual population and employment as reported in the census. The results indicate that building floor space, together with the city level aggregate information of building morphology, the density coefficient, demographic attributes, and real estate statistics, are able to generate a reasonable estimation.

Keywords: transit-oriented development; fine geographic space; developing country; geographic information system

1. Introduction

Both macro scale comprehensive regional and corridor planning, and local level station area planning, are among the key frameworks highlighted for urban policy intervention in transit-oriented development promotion. At the station area level, general urban design guidelines for transit-oriented development and smart growth [1–3] suggest that compact urban areas form around the station area district, which accommodates a fairly dense population. Employment is essential for a successful transit-oriented development. The idea is that by encouraging more people to live and work within the geographic advantage of good accessibility and close proximity to transit stations, more people are expected to travel using transit as opposed to their personal vehicle. As a result, it helps cities reduce private automobile dependency and solve traffic congestion issues as well as generate various environmental, economic, and social benefits for better urban sustainability [4]. Additionally, it assists transportation agencies to attain substantial passenger ridership to ensure the cost-effectiveness of expensive transit investments [5].

Basic information on station area population and employment serves as important input for research to yield valuable evidence to support transit-oriented development appraisals. The application of the data on the number of residents and employees around the station area can be observed in various applied and theoretical transit-oriented development studies, such as density benchmarking [6,7], accessibility [8–10], typology classification [11–13], transit feasibility study [5], passenger ridership [14–17], and the design guideline and development framework [18–21].

To obtain the information of the station area population and employment, most studies have derived their data from the census tract [5–11,13,14,16,17] or even block [12,15]. The smaller geographical census unit is presented by the census bureau. However, generating station area population and employment information is never easy for cities of developing countries where detailed census data may not be readily available and may often be difficult to access. For example, the most detailed census data published by the Department of Statistics, Malaysia [22] for the capital city of Kuala Lumpur in Malaysia are at the census district level. On average, the geographic size of each census district of Kuala Lumpur has an area of 3028 hectares. In comparison to the census tract or block in advanced economies, these census districts are spatially too large and coarse for providing station area population and employment data. In answering the challenge of the official population and employment data deficit at a fine grained geographic scale in the digital age today, many studies of the related research have focused on the exploration of big data arising from our personal mobile phone as a promising option. The high diffusion rate of the mobile phone phenomenon together with the continuous growth of massive datasets from call record, social network, web browsing, and granular geo-location sensor data point generated from the mobile phone of each individual, mobile phone big data offers a fascinating opportunity and possibility for researchers to trace the physical presence of human activities and reflect the population density dynamically for a given geographic space [23]. To name a few, Ratti et al. [24] explored the location based services data from the mobile phone use to analyze the intensity of urban activities through space and time in the metropolitan of Milan, Italy. Deville et al. [25] exploit extremely large datasets of mobile phone call records (more than a billion) from the spatial scale of the radio coverage of the base station to map the detailed temporal variation of day time population over Portugal and France. Dong et al. [26] apply the mobile phone data to identify and aggregate the number of employees from the major company workplace (at building level) to assess the national economic activity in China. Chen et al. [27] employ mobile phone data as a dynamic method to measure real time local population exposure to the atmospheric particulate matter that has a diameter fewer than 2.5 micrometers. More importantly, mobile phone big data has been validated by empirical studies that it is useful for human activities estimation in the refined spatial resolution [25,28–31] and the further classification into the detail category of home-related and work-related activities [32] as well as a certain level of the demographic profile [33] via machine learning is possible.

With a growing body of evidence from the big data research studies during the last decade, national statistical institutions of numerous developed nations from Europe [34,35], the United States [36], Australia [37], and China [38] (an exceptional case of developing nations) are acknowledging the opportunities of big data and are keen to harness big data as new data sources, either complementing or substituting for the expensive traditional data sources of paper-based surveys in official statistics. Despite the positive outlook of big data, using big data in official statistics remains a great challenge [39–41]. This is not only limited to developing countries but even developed countries are facing this problem too [34]. Several utmost drawbacks include methodology, quality, and privacy. First, unlike the conventional questionnaire survey data, big data sources such as mobile phone data are diverse and unstructured in nature, which are not designed to serve any objective [42]. Therefore, the traditional statistical technique is no longer appropriate in the context of big data. Innovative knowledge of new methodology is required to process the big data into meaningful statistical information [42,43]. The second concern is that the statistic quality based on big data is questionable. For instance, identifying human activities using mobile phone data has a few constraints since someone could have more than one mobile phone or none, children may carry a mobile phone that belongs to their parents or guardians, mobile phones may be switched off due to a weak battery cell, and many more reasons [27,30,34]. This situation could introduce noise and error into the result. Third, big data contains an enormous amount of sensitive and personal information. Even if it is protected with adequate legislation, it is difficult to guarantee that the data is never wholly immune from cybersecurity risk [34,39–42]. This could raise public unease on their privacy issues, which hinders organizations from leveraging big data.

As a matter of fact, presently, most authors do not provide any definitive answer on the application of big data but rather place themselves in a neutral position to carefully debate the promises and limitations of big data [39–45]. Furthermore, the recent study on the assessment of big data for official statistics in the Caribbean reported that the small island developing states in this region are not ready for the idea of big data considering the shortcomings of methodology, quality, technology, data access, legislation, privacy, management, and finance that have to be addressed [46]. From the discussion above, it is clear that the popular big data approach seems uncertain and it might be too early for developing countries to adopt at this moment. Therefore, since this research aimed to estimate population and employment at the fine geographic scale of station area for transit-oriented development promotion in the context of cities of developing countries, we do not find mobile phone big data appropriate for this study. To overcome this issue, this paper attempts to investigate the application of the building floor space as an alternative technique to estimate the station area population and employment. First, the paper reviews current approaches and the possibility of applying building floor space to estimate population and employment in the context of a finer geographic scale. Section 3 defines the size of the station area in this research study and demonstrates our proposed methodology. Section 4 introduces our study area and illustrates data input for the estimation. Section 5 discusses and verifies our estimation results together with the census block reference data. The final section concludes on the applicability of the proposed technique and its limitation.

2. Background

The research results from the regression analysis of Lwin and Murayama [47] and Biljecki et al. [48] suggested that building floor space has a strong, positive, and linear correlation with population. This study found that the total building floor space within a particular geographic area has a meaningful association with the number of the population in the area. Based on their findings, it also implies that a greater amount of building floor space provides a clue of larger numbers of population. Conversely, a lesser amount of building space signifies smaller numbers of population in a given location. In fact, previous studies are found in the building floor space experiment for a fine geographic scale population estimation [47,49,50]. Lwin and Murayama [47] use building floor space and the census tract to build an empirical weighting model to map the population distribution at the scale of the building. Alahmadi et al. [49,50] estimate the population size of a neighborhood by using building floor space and the block level empirical statistical model of inhabitants per dwelling unit. However, applying these approaches to the station area in cities of developing countries remains difficult. This is because the detailed census and local statistic data in the earlier section are seldom available in developing countries. Thus, no realistic empirical model can be established for these cities to transform building floor space into the population. In addition, the existing studies are mainly focused on the residential building floor space for population estimation in the context of a relatively homogenous housing environment. However, efforts on the research extension into non-residential building floor space (e.g., commercial, institution, and industrial) for employment estimation and the environment of an urban setting where the transit development that tend to take place is rarely discussed. To address these gaps, we suggest for the building floor space approach to incorporate ancillary variables by performing the population and employment estimation on the selected urbanized station areas in Tokyo, Japan.

As part of a long-established custom, building floor space together with ancillary variables has been widely accepted in development planning studies (at both micro and macro levels) for forecasting the potential future population and employment implications for environmental, economic, and social assessments. These studies' findings provide a basis for suggesting recommendations to mitigate possible anticipated consequences of development planning. Conner Holmes [51] forecasts population and employment from the proposed Wilton Junction new township masterplan for the land supply and infrastructure planning. The City of Calgary [21] analyzes the population and employment growth scenarios of the Brentwood Station Area potential development for the mobility assessment. Japan International Cooperation Agency [52] forecasts future population and employment of Kabul Metropolitan to analyze the residential, commercial, and industrial land supply to meet upcoming demand. These studies apply the planned building floor space from the city's proposed master plan to forecast future population and employment. Nonetheless, these development planning studies are more about future forecasting rather than current estimation, and their results are rarely validated. This may be due to the absence of proper references such as the census for them to check against. Therefore, there is little evidence on the efficacy of building floor space in providing a good estimation of existing population and employment of an urban area. Consequently, it becomes highly essential to systematically test and verify the use of building floor space for urban area – in our case here, transit area – population and employment estimation. This is because an inaccurate station area population and employment estimations may lead to significant implications on financial and economic risks of transit-oriented development.

Based on our knowledge, in transportation studies, Priemus et al. [53] found that rail passenger forecasts are often inaccurate and biased, with an average overestimation of about 106 percent. At this point, we could only presume that forecasts tend to be imprecise and overestimated to provide minimal risk measures such as propping up transportation project proposals. Furthermore, it is interesting to observe that there have not been unified variables being adopted by various studies on the building floor space approach for population and employment forecasting. We believe that, by better rationalizing and refining the present building floor space approach to incorporate additional variables in the transformation procedure, better estimations could be yielded. To test our hypothesis, we, therefore, evaluate the application of building floor space with different variables in the station area population and employment estimation. The specification of the model is illustrated in Section 3.2.

While this study attempts to estimate the station area population and employment by using building floor space, it is worth noting that the application of remote sensing for population estimation at a finer geographic scale such as the individual housing and street block level is possible [54]. Physical characteristics extracted from satellite imagery or aerial photographs have been used for deriving the population data. As early as the 1950s, Green [55], Hadfield [56], and Binsell [57] estimated a population based on simple dwelling counts from aerial photographs. With the advancement of high resolution remotely sensed imagery and processing technologies in modern days, the building footprint [58], the building rooftop areas [59], and the building volume [60–64] are employed to estimate the population. In addition to remote sensing, Biljecki et al. [48] adopt a different approach of using a sophisticated detailed semantic 3D city model to generate population estimations. It is, thus, observed that, to date, approaches to population estimation have been well researched but little has been done with respect to employment estimation. Since this study concerns both population and employment estimations of station areas, a slightly different approach needs to be explored.

3. Methodology

This section defines the spatial properties of station areas in the context of this research and discusses the details of the building floor space approach for estimating the station area population and employment.

3.1. Station Area Definition

The station area, which is sometimes referred to as the transit catchment area or service coverage, is a geographic space around a station that offers physical proximity for people to access the transit service. The size of the station areas typically varies according to their transit service and the mobility options of transit users. Nevertheless, many guidelines suggest ideal distances of 400 m (1/4 mile) to 800 m (1/2 mile) from the station, based on the pedestrian shed. The top priority is given to pedestrians since walking is the fundamental and socially equitable form of travel mode for the general transit user. Therefore, living and working within a close vicinity of the station is crucial, as it eases people's movement especially on foot. Daniels and Mulley [65] reveal that a large portion of people (75 percent) in Sydney are willing to walk up to 800 m for the rail service. Meanwhile, in the warm tropical context of Malaysia, Diyanah et al. [66] find that residents of different age groups from Putrajaya, Shah Alam, and Sabak Bernam are willing to walk up to 400 m. Additionally, Guerra et al. [67] examine the relationships between the catchment area and transit ridership at 1500 stations in 21 cities across the United States and indicate that land uses within a 400 m radius have a stronger effect on transit ridership in comparison to 800 m. The results from these studies give us some credence to use 400 m as the radius to define station areas for this study.

3.2. Population and Employment Estimation Models

In order to compare the application of building floor space with different variables in estimating the population and employment size, we constructed four models using various combinations of variables. Since the interaction between variables and models are multidimensional in this research, the matrix diagram method is applied to aid our evaluation procedure on the performance of these building floor space models, which correspond to the set of variables. The matrix diagram method is a useful tool that allows a complex relationship situation to be effectively analyzed and visualized in a legible way [68,69]. Importantly, it offers an advantage to look at specific combinations, determine essential factors, and explain the relationships between results, causes, and methods [70,71]. The matrix diagram of this research, as shown in Table 1, based on the symbols, the checkmark denotes the presence of a particular variable in the building floor space model and a cell with a hyphen is a sign of absence.

Table 1. Different combinations of variables used for experimenting building floor space in the station area population and employment estimations.

Variables	Model A		Model B		Model C		Model D	
	Pop.	**Emp.**	**Pop.**	**Emp.**	**Pop.**	**Emp.**	**Pop.**	**Emp**
Gross Floor Space	✓	✓	✓	✓	✓	✓	✓	✓
Net-to-Gross Floor Space Ratio	-	-	-	-	✓	✓	✓	✓
Net Floor Space per Dwelling Unit	✓	-	✓	-	✓	-	✓	-
Household Size	✓	-	✓	-	✓	-	✓	-
Net Floor Space per Employee	-	✓	-	✓	-	✓	-	✓
Occupancy Rate	-	-	✓	✓	-	-	✓	✓

Note: Pop. = Population. Emp.= Employment.

Among the four building floor space models, three models (A, B, and C) were based on the existing forecasting studies (Table 2) whereas Model D was our proposed, refined approach. In this way, we can directly compare the quality of estimations given by these models. For population estimation, we considered (i) gross floor space, (ii) net-to-gross floor space ratio, (iii) average net floor space per dwelling unit, (iv) average household size, and an (v) occupancy rate. On the other hand, (i) gross floor space, (ii) net-to-gross floor space ratio, (iii) average net floor space per employee, and (iv) the occupancy rate were taken into account for employment estimation.

Model A is a simple approach for estimating population and employment. The model pays no attention to the detailed features of building floor space (i.e., gross vs. net). Gross floor space is the basic total floor space within the building envelope while net floor space is the subset of gross floor space without including unoccupied public spaces such as corridors, stairways, washrooms, parking garages, utility rooms, and mechanical closets. Model A computes population estimation by translating residential gross floor space with net floor space per dwelling unit and average household size. For the case of employment estimation, Model A implies commercial, institution, and industrial gross floor space directly with net floor space per employee. Meanwhile, Model B is fairly similar to Model A, with the exception of an additional variable of an occupancy rate. The occupancy rate refers to a used space ratio compared to the total amount of available space.

Table 2. Summary of modeling approaches and present population and employment forecasting studies using building floor space.

Modeling Approach	Author(s)	Study Area	Geographic Scale	Purpose of Study
Model A	Watson & Associates Economist Ltd [72]	Waterloo, Canada	City-wide	To review the development charge with the forecasted public facilities to serve the new development.
	County of Riverside [73]	Riverside County, United States	County	To appraise the population and employment growth from the general plan for socioeconomic, transportation, environment, public infrastructure, and facility planning.
	SGS Economics and Planning [74]	Parramatta, Australia	Precinct	To evaluate the implication of the city center master plan against the projected economic growth and housing demand.
	Connor Holmes [51]	Wilton Junction, Australia	Township	To analyze the land use supply and infrastructure planning of the new township proposal to meet the future forecasted population and job demand.
	District of Mission [75]	Mission, Canada	City-wide	To study commercial and industrial land availability to meet the future labor force demand.
Model B	Strategic Regional Research Alliance [76]	Greater Toronto Area, Canada	Metropolitan	To examine the impact of regional express rail development on the jobs and housing growth around the transit stations.
	City of Woodland [77]	Woodland, United States	Township	To evaluate the environment effects of potential population and employment growth from the general plan.
Model C	City of Calgary [21]	Brentwood, Canada	Precinct	To assess the traffic impact of the station area redevelopment plan.
	Japan International Cooperation Agency [52]	Kabul Metropolitan, Afghanistan	Metropolitan	To analyze the land use plan to meet the need for regional expansion.

Model C is a more advanced approach in population and employment estimation. Built upon the basic structure of Model A, Model C interprets gross floor space into population and employment with cautious consideration of both gross and net floor spaces. To convert the gross floor space into net floor space, a net-to-gross floor space ratio is applied in Model C. The gap between net and gross floor spaces becomes increasingly noticeable from low-rise to high-rise buildings [78,79]. Apart from the above, Model D is the most detailed approach that applies all relevant variables used in Models A, B, and C. We applied these four models to estimate the population and employment of five station areas in Tokyo. The estimation results obtained from these models were then verified with the actual population and employment data reported in the census.

4. Study Area and Data

To test the building floor space approach, we employed five station areas namely Toyosu, Etchujima, Tsukishima, Kachidoki, and Kiba in Tokyo as our empirical case study (Figure 1). They were selected based on the presence of a considerable mixture of jobs and housing composition in the urban environment setting. For this study, we examined the application of building floor space in both population and employment estimations concurrently. Furthermore, this is also suitable for developing countries since the mass transit infrastructure investment largely focuses on the urban settlement. The size of each of these station areas is about 50 hectares, which is an area defined by the 400 m

Euclidean distance measured from the station (see Section 3.1). The numbers of population and employment obtained from the official census block for the five station areas are shown in Table 3. This information will be used as the basis to validate the estimation results.

Table 3. Population and employment of Toyosu, Etchujima, Tsukishima, Kachidoki, and Kiba station areas.

Station Area	Population [1]	Employment [2]
Toyosu	13,989	21,116
Etchujima	5166	4556
Tsukishima	16,463	6808
Kachidoki	14,934	8124
Kiba	8794	15,663

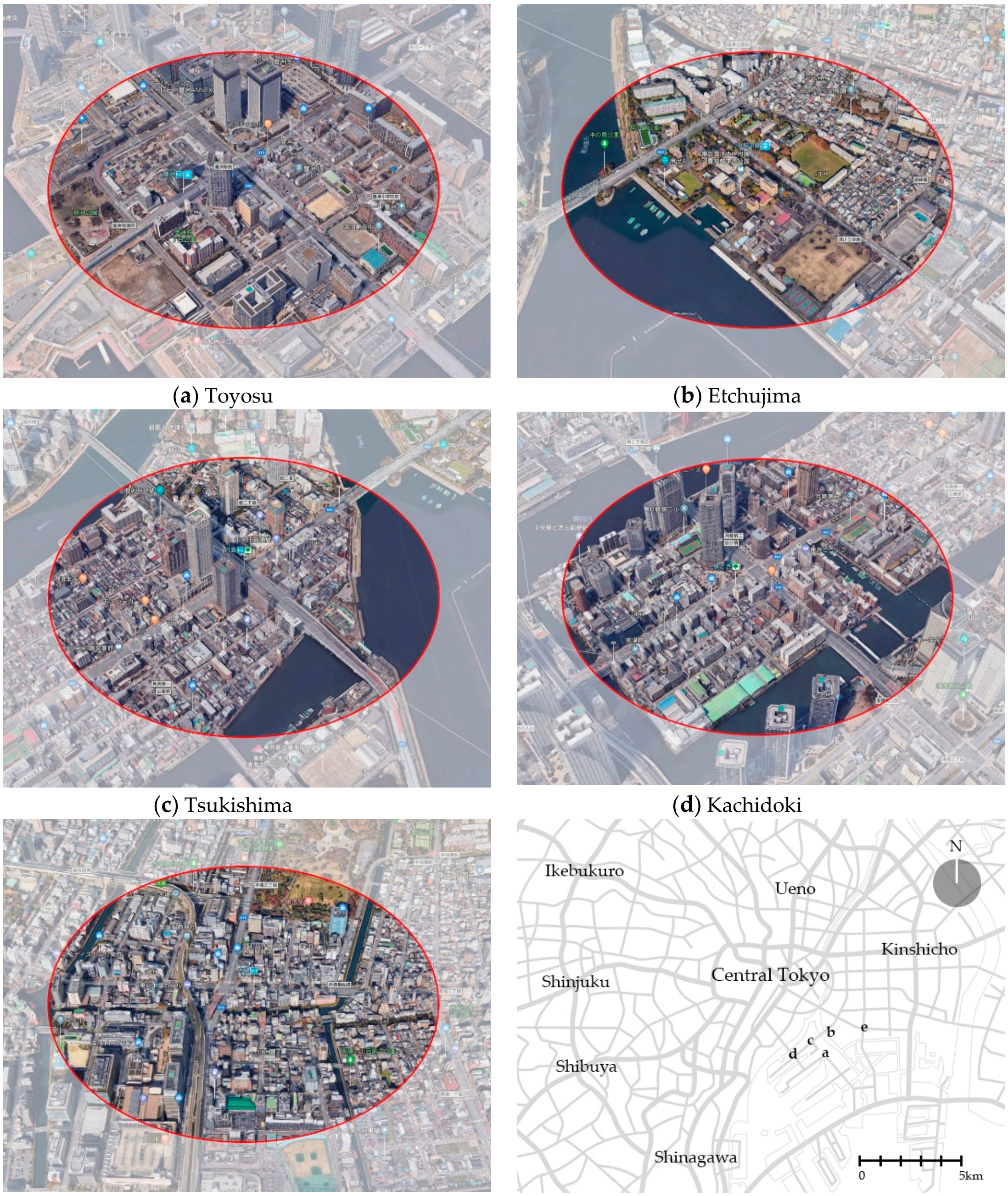
[1] [80]; [2] [81].

The entire amount of gross floor space in each of our study areas (as summarized in Table 4) is assembled from the gross floor space of each building located in the station area vicinity. To produce the building gross floor space, we derived them by using the official Tokyo Metropolitan Government administrative GIS database that contains a building polygon with attribute information of the building footprint, the number of building floor, the gross floor space, and the classification of building use. Using GIS proximity tool, a total of 3,968 building polygons from five station areas are captured from the dataset for this study. Since our research applies the Euclidean distance principle, subsequently, not all building polygons have precisely fallen within a 400 m radius of the station area buffer. To acquire the gross floor space for the building polygons that partially intersect at the perimeter of the station area, we relied on their weight (based on the proportion of the building footprint size area).

Due to the detailed attribute documentation, where the amount of floor space per usage activity per building is well established by the city administration, we are able to distinguish and quantify the gross floor space variation of mixed-use building of our study area. Elsewhere, we would refer on the robust technique of Greger [82] by adopting the building footprint area and the number of the building floor to generate the building gross floor space, as well as rely on the number of the address point from the open access business directory to assign the usage fraction and approximate their respective gross floor space quantity in the mixed-use building. In the GIS database, the identified apartment tower with ground-floor retail, both residential and commercial gross floor space will be extracted and sorted into two different group. Nevertheless, we carried this procedure manually for every single mixed-use building polygon of our study area. It took us a while to complete the process for these five station areas because the multi-activity building is common in urban areas. Even with a few mistakes observed during our preliminary computation, particularly on the building polygon of high-rise building, it has resulted in a significant error in our station area population and employment estimation. Therefore, it should be done with caution. In view of applying this method for the cities of developing countries where their building use classification may not be as complex as our study area at this moment, we begin with four basic categories of floor space activity (i.e., residential, commercial, institution, and industrial) for this research study. Therefore, the given 15 detail classification of building uses from the official data are reorganized into the previously mentioned categories (see Appendix A). Since agriculture, forestry, and fishery building use is hardly ever notice in an urban setting when compared to the countryside, we do not include it in our study. An example of the improvised GIS building floor space data of Toyosu station area for this research is displayed in Appendix B.

Table 4. Estimated total gross floor space of Toyosu, Etchujima, Tsukishima, Kachidoki, and Kiba station areas.

Station Area	Estimated Total Gross Floor Area (sq. m)			
	Residential	Commercial	Institution	Industrial
Toyosu	578,098	631,139	20,442	3389
Etchujima	281,239	123,472	20,442	13,800
Tsukishima	738,100	122,505	42,060	14,440
Kachidoki	775,820	208,320	69,910	25,159
Kiba	425,943	325,754	14,404	13,728



(**a**) Toyosu (**b**) Etchujima (**c**) Tsukishima (**d**) Kachidoki (**e**) Kiba (**f**) Location Map

Figure 1. An overview of the study area [83–87] and its geographic location in Tokyo City.

Meanwhile, values of the variables for the five station areas' population and employment modeling were assumed to be similar to that of the Tokyo Metropolitan aggregate statistics. These data were obtained and adapted from official statistics, research studies, real estate market reports, and guidelines. Net-to-gross floor space ratio for residential, commercial, institution, and industrial buildings were set to the value of 0.75, 0.75, 0.75, and 0.90, respectively (see Table 5). In the building economic guides from Johnson [88], the commonly accepted ratio for residential buildings (apartments) is 0.64, while that of commercial (retail and office) ranges between 0.7–0.8, the institution (school, hospital, and library) ranges between 0.55–0.76, and the industrial ranges between 0.85–0.93. Since the space efficiency of buildings in Tokyo is relatively higher than those in Western countries (due to the smaller parking space requirement), a higher value of net-to-gross floor space ratio from the guides are adopted. Average occupancy rates for Tokyo's residential, commercial, institution, and industrial properties reported by the real estate market research were applied for our study area. For the case of net floor space per employee, these values were adjusted to the Japanese cities' context with reference to the employment density guide prepared by the British Homes and Communities Agency [89]. We recognize the size difference of working space between Tokyo and the cities of North America and Europe. Miller [90] discovers the median net office floor space per worker in American cities to be about 25 sq. m, while in Japanese cities it is less than 15 sq. m. We considered the average net floor space per dwelling unit in Tokyo at 65 sq. m., with an average household size of 1.94 persons as documented by the Statistics Bureau of Japan [91] and Tokyo Metropolitan Government [92].

Table 5. Data input for the population and employment estimation of five station areas in Tokyo in 2015.

Variables	Residential	Commercial	Institution	Industrial
Net-to-Gross Floor Space Ratio	0.75 [1]	0.75 [1]	0.75 [1]	0.90 [1]
Occupancy Rate	0.96 [2]	0.98 [2]	0.98 [2]	0.97 [2]
Net Floor Space per Employee (worker per sq. m)	-	20 [3]	35 [3]	50 [3]
Net Floor Space per Dwelling Unit (unit per sq. m)	65 [4]	-	-	-
Household Size (residents per dwelling unit)	1.94 [5]	-	-	-

[1] [88] (p. 155). [2] [93,94]. [3] [89,90]. [4] [95]. [5] [91,92].

5. Results and Discussion

We carried out the experiments and benchmarked them against actual governmental census data. The results show a large degree of differences between the accuracy depending on the models and the variables considered. The results of the experiments are presented in Table 6. Based on what we expected, the smallest mean absolute percentage error is observed in our proposed detailed Model D, registering a difference of 9.51% for the population estimation and 16.30% for the employment estimation. However, it is surprising to note that Model C is only slightly less accurate than Model D. It seems that the occupancy rate does not add much value to the model. This could be due to the higher tenancy level in our study area, which gives rise to negligible effects on the results. Likewise, a similar trend can be observed between Model B and Model A, which both lack input on the occupancy rate. This finding lends support to estimations in station areas with a high tenancy level while the occupancy rate data are not available.

Furthermore, it is noted that the mean absolute percentage errors from Models A and B are much higher than Models C and D. Scatter plots from Figure 2 also display that, in most cases, the station area population and employment estimations from Models A and B deviate much further from the actual census data. Models C and D yield better estimations over that of Models A and B because they consider the net-to-gross floor space ratio. The variable helps exclude unoccupied common spaces such as the lobby, corridor, utility room, and garage, which are not related to net floor space per dwelling unit and net floor space per employee.

Table 6. Tokyo's five station areas' population and employment estimation accuracy assessment results.

Station Area	Model A		Model B		Model C		Model D	
	Pop (%)	**Emp (%)**	**Pop (%)**	**Emp (%)**	**Pop (%)**	**Emp (%)**	**Pop (%)**	**Emp (%)**
Toyosu	+23.34	+52.53	+18.41	+49.48	−7.50	+14.45	−11.20	+12.16
Etchujima	+62.48	+54.38	+55.98	+51.23	+21.86	+16.70	+16.99	+14.31
Tsukishima	+33.81	+11.86	+28.46	+9.59	+0.36	−15.46	−3.66	−17.19
Kachidoki	+55.05	+58.99	+48.85	+55.75	+16.29	+20.17	+11.64	+17.71
Kiba	+44.56	+8.37	+38.78	+6.18	+8.42	−18.46	+4.08	−20.11
Mean Absolute Percentage Error (%)	43.85	37.23	38.10	34.45	10.89	17.05	9.51	16.30

Note: Pop. = Population. Emp.= Employment '+' and '-' represent over-estimation and under-estimation, respectively.

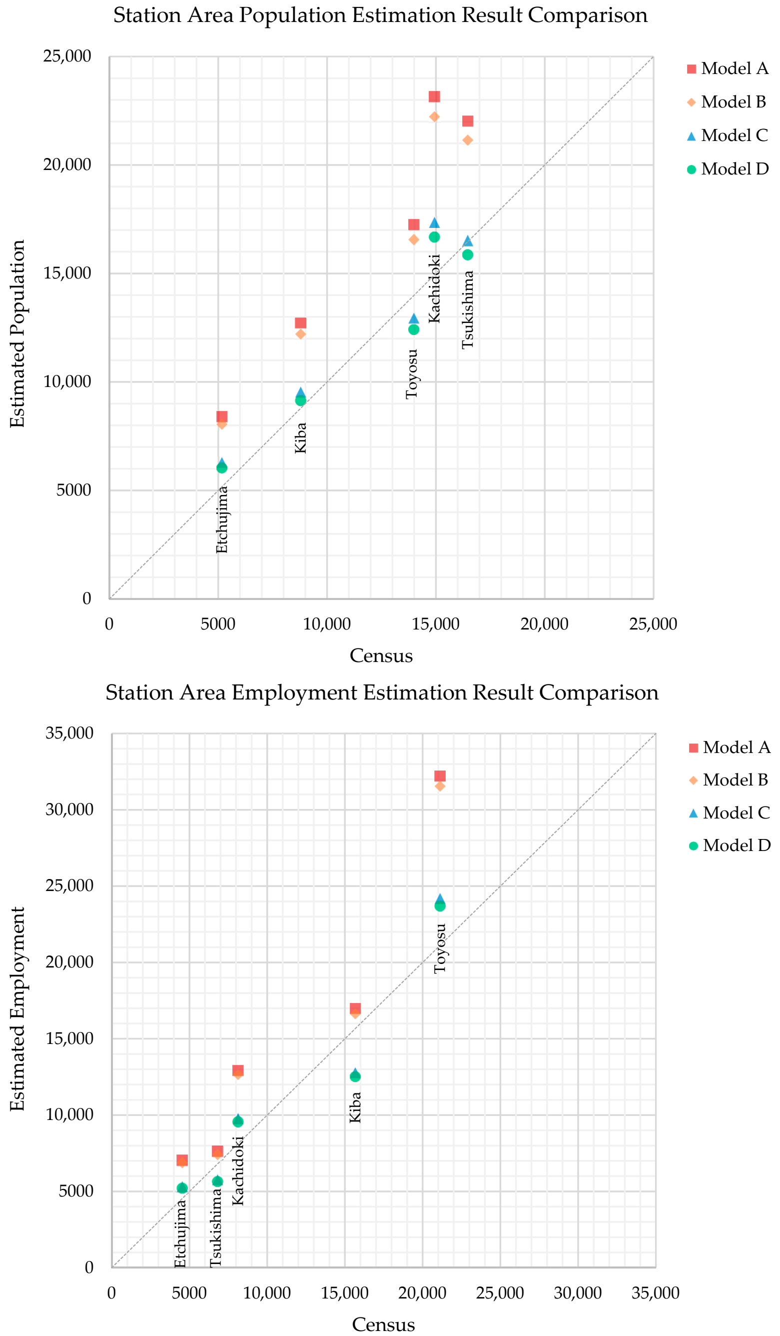


Figure 2. Scatter plots of the estimated counts versus census-based counts: population (top) and employment (bottom).

Thus, the net-to-gross floor space ratio provides a significant improvement in its estimations over the models lacking such information. This finding suggests that a net-to-gross floor space ratio is necessary for the building floor space model to achieve accurate estimations of population and employment. While the net-to-gross floor space ratio is crucial, it appears that there is inconsistent performance across the five station areas. In comparison to Models C and D, Model B is noted to have good employment estimation for Tsukishima and Kiba station areas even without the information on the net-to-gross floor space ratio. In this study, it is premature for us to explain the reason why, in this particular model, lesser data yielded better results because all the errors (induced by quality of input data, homogenous assumptions for all entities in our study area, etc.) have been aggregated in a single number that cannot be decomposed. A potential way to investigate this phenomenon is to attain fine grade local statistics data for the model as well as conduct more case studies to obtain the mean error.

In most cases, we notice that employment estimations tend to suffer from higher discrepancies over the population estimation. A possible reason is that the variation among the working space configuration (office, retail, finance, restaurant, entertainment, hotel, education, healthcare, manufacturing, storage, etc.) is far more wide-ranging and complex than the housing space pattern (apartment, detached, studio, etc.). We were expecting that these errors would be absorbed within the statistical variations of different entities in the station area, but it turned out to be different. This indicates that, by simply generalizing such diverse characteristics of working space into the three broad categories of commercial, institution, and industrial is insufficient. Thus, future studies may consider improving the model by further expanding and refining the employment building floor space classification.

Compared to the related work on finer scale population estimation in urban settings by using remote sensing, the finer building floor space approach (Models C and D) provides a closer approximation of population, recording mean absolute percentage errors at 10.89% and 9.51%, correspondingly. By comparison, the accuracy assessment of population estimation by Wang et al. [64] with building volume for the sub-district registers an error of 16.46%, while the error of population estimation at half size of artificial blocks (an artificial block consists of 20 census blocks) via building volume and census block level housing statistics by Wu et al. [60] is documented at 15%. Using building volume associated with the spatial autoregressive model, the census block level population estimation by Qiu et al. [61] yields an error of 23.74%. At the neighborhood level, Xie et al. [63] observe a population estimation error at 33.12%. This gave us another insight that using building floor space (m^2) could achieve better estimation than building volume (m^3). We think that building volume is incapable of isolating the internal void space such as atrium and the lower ground floor in the building. As a consequence, given a similar set of the building (with identical function and geometry), the building volume may produce a different result as compared to building floor space. However, it should be noted that building floor space may not always be superior than building volume. For instance, the building volume approach has the automated computational advantage over the manual extraction of the building floor space approach to eliminate possible human error.

Drawing on the results from the above studies, it may be suggested that considering building floor space together with the additional information of building morphology (net-to-gross floor space ratio and net floor space per dwelling unit), density coefficient (net floor space per employee), demographic attribute (household size), and real estate statistics (occupancy rate) can provide a satisfactory population estimation. Due to the fact that the employment estimation study is relatively uncommon, we are unable to evaluate the accuracy of our employment estimation from building floor space and provide a valuable discussion yet.

6. Conclusions

This study explores the application of the building floor space approach for the station area population and the employment estimation. We demonstrate this method using five station areas in Tokyo that are characterized by jobs and housing diversity. The findings from the study indicate that, under certain circumstances, the building floor space can offer a good estimation of population and employment. Since detailed census data are rarely available in most developing countries, it is believed that this approach can serve as a potential tool for providing important station area population and employment information for architects and civil engineers to support transit oriented development. Additionally, the methodology presented in this research could also be helpful for many other domains where fine spatial scale population and employment data is essential. This includes public facility planning [96], disaster and hazard management [97], disease response [98], and market analysis [99].

The advantage of the building floor space approach is that it does not involve much laborious, expensive, and time consuming field surveys to obtain the station area population and employment counts. Building floor space can be derived from the GIS database remotely and data input for the variable is based on publicly available city level information. Given that the cost of information technology products has fallen over the past several decades, GIS is getting affordable and gradually adopted by developing countries in urban development and planning [100,101]. With the additional decrease in the cost of data storage infrastructure (by means of cloud computing system) [102,103] and the emergence of a respectable quality of open-source GIS software (such as QGIS and gvSIG) over the mainstream proprietary GIS software (ArcGIS) [104,105], we are expecting that the diffusion of GIS could further accelerate in developing countries. Hence, it is not surprising that the GIS database includes land use maps, planning applications, and building floor plans for the purpose of urban planning and is getting increasingly available in the cities of developing counties. Considering the increasingly favorable GIS application in urban planning in developing countries, the generation of high quality building floor space data is promising. Therefore, using the building floor space approach to estimate station area population and employment is beneficial for cities of developing countries where financial resources for conducting detailed census counts are limited.

The key constraint of our study is the small sample size (five station areas). Consequently, it restricts us from generalizing and providing conclusive evidence. Our study consists of exploratory research aimed to experiment with an alternative approach that has not been adequately explored. Conservatively, at least for this moment, our study results illustrate the building floor space approach could offer a potential application for estimating station area population and employment. Furthermore, the insights from this study would able to create awareness and prove that further investigation is necessary and worthy. It is our hope to continue this work in the future by expanding our sample size.

In addition, our study is limited with the adoption of homogenous city level information for variable data input for all station areas. This would not be able to reflect the complex environment in our reality. For example, the average household size in our study area has been assumed to be same with the average household size of Tokyo City. Rationally, we would expect that the household size varies among the dissimilar dwelling sizes and patterns according to demographic and socioeconomic characteristics. Even though our estimation shows that the application of homogenous city level information is sufficient to generate satisfactory results, it should be noted that our results are merely based on five station areas and it is still too early to conclude on the reliability of such methodology. We can assure that our estimation results could improve considerably if local neighborhood specific statistics are adopted. Yet, this would involve additional resource. Therefore, it is worthwhile for future studies to examine the cost effectiveness of using multiple fine grade local statistics data to improve the accuracy of the building floor space approach for estimating the station area population and employment.

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Appendix A

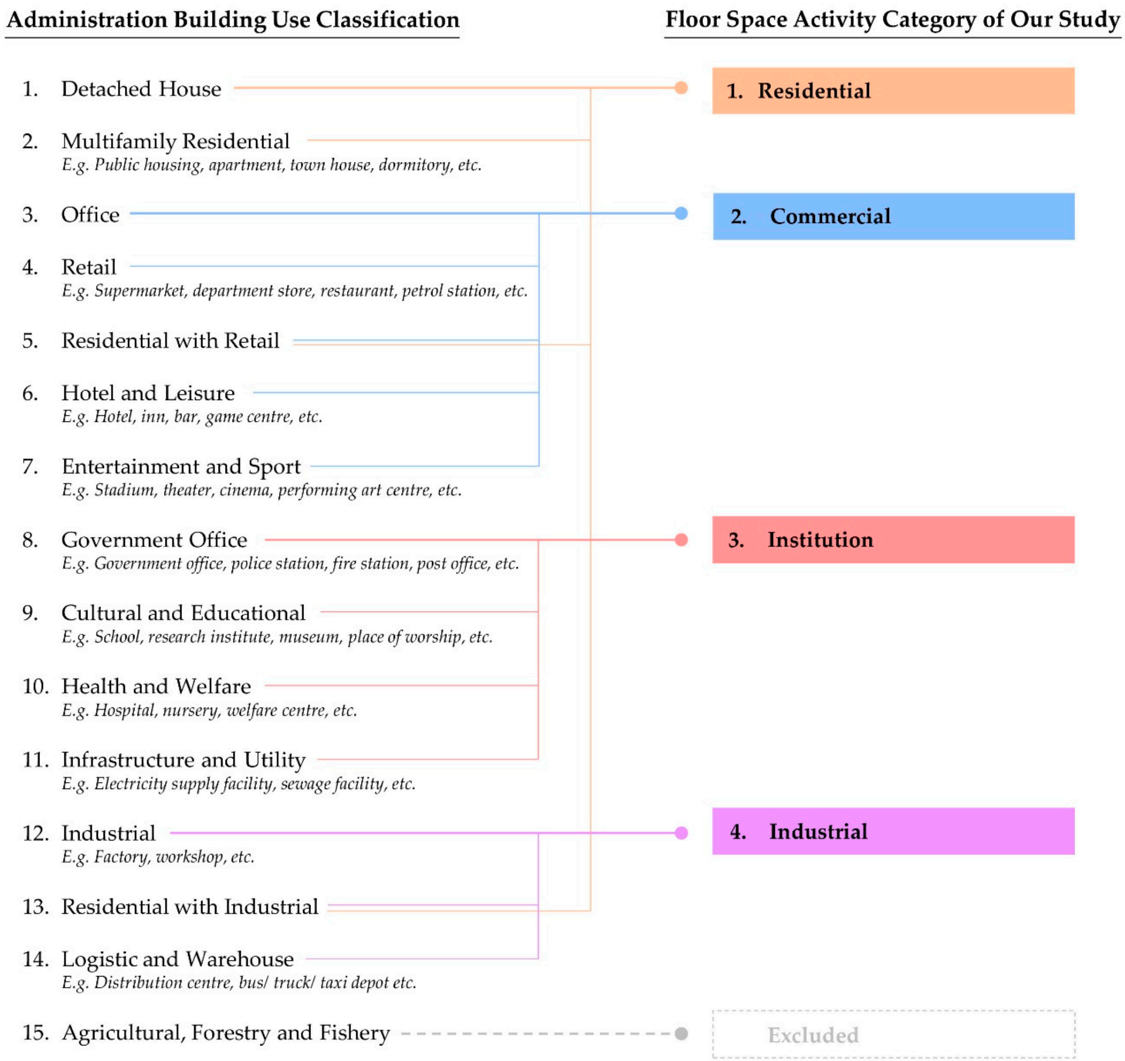

Figure A1. The revised floor space activity category from the administrative building use classification.

Appendix B

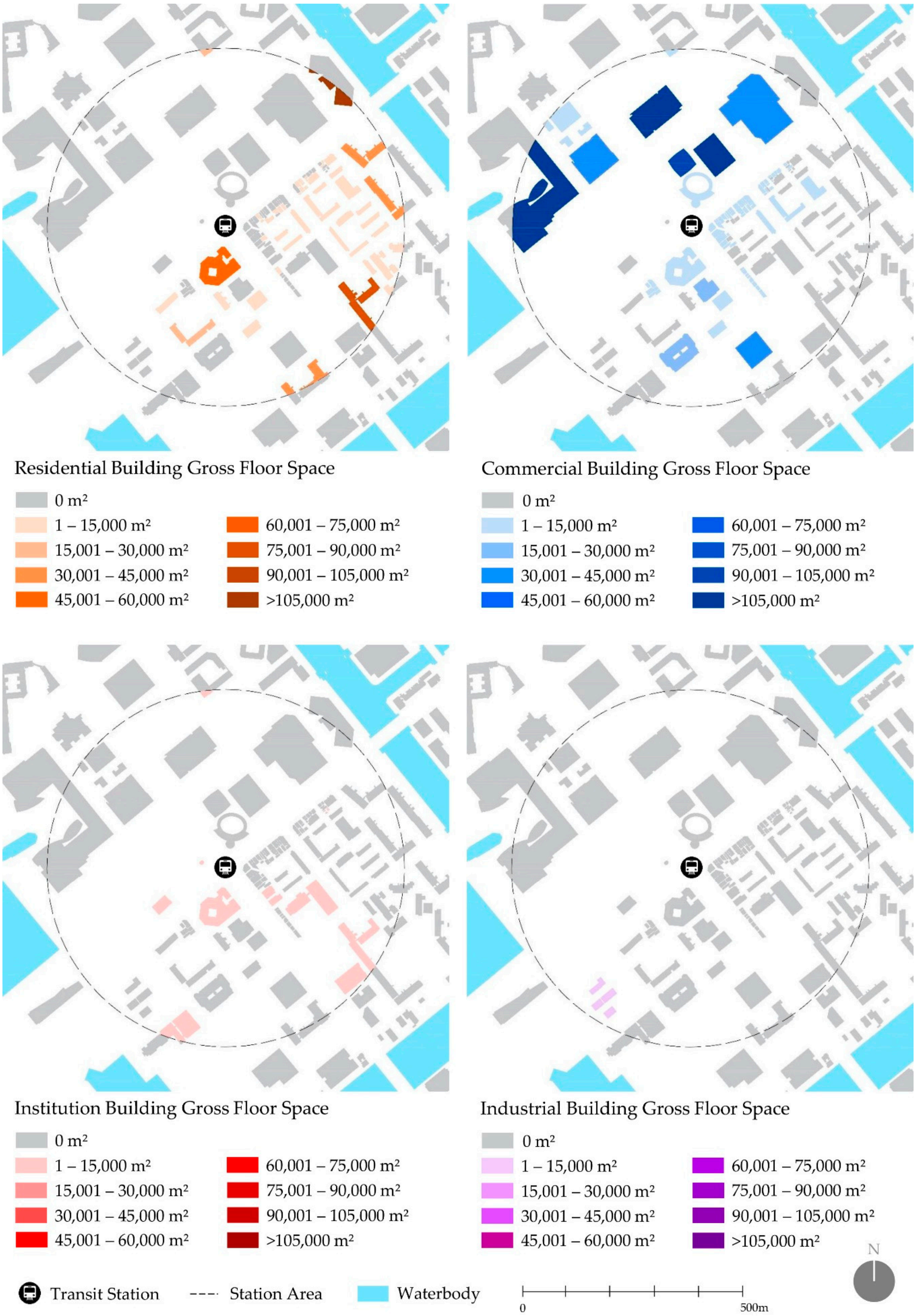

Figure A2. A series of visual maps illustrate the detailed gross floor space distribution (residential, commercial, institution, and industrial) among the buildings of the Toyosu station area in 2015.

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