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Population Allocation at the Building level for Micro-level Urban Simulation: A Case of Jeonju, Korea

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Abstract It is important for urban planners and policy makers to understand complex, diverse urban demands and social structure, but this is not easy due to lack of data that represents the dynamics of residents at micro-geographical level. This paper explores how to create population data at at a micro-level by allocating population data to building. It attempted to allocate population data stored in a grid layer (100 meters by 100 meters) into a building footprint layer that represents the appearance of physical buildings. For the allocation, this paper describes a systemic approach that classifies grid cells into five prototypical patterns based on the composition of residential building types in a grid cell. This approach enhances allocation accuracy by accommodating heterogeneity of urban space rather than relying on the assumption of uniform spatial homogeneity of populations within an aerial unit. Unlike the methods that disaggregate population data to the parcel, this approach is more applicable to Asian cities where large multifamily residential parcels are common. However, it should be noted that this paper does not demonstrate the validity of the allocated population since there is a lack of the actual data available to be compared with the current estimated population. In the case of water and electricity, the data is already attached to an individual address, and hence, it can be considered to the purpose of the validation for the allocation. By doing so, it will be possible to identify innovative methods that create a population distribution dataset representing the comprehensive and dynamic nature of the population at the micro geographical level.

Keywords population allocation, prototypical patterns, disaggregate populations to building, buiding index

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I. Introduction

Urbanization predominantly results in the horizontal or vertical growth of urban areas. According to the United Nations, 55.3 percent of the world population lived in a city in 2018, and it was projected that about 60 and 70 percent of the world population would live in a city by 2030 and 2050, respectively (U.N., 2019). While cities have physically grown, an urban phenomenon associated with the ecology of cities have become complicated. The emergence of a new, complex urban ecology requires to integrate a diversity of approaches from a broad set of disciplines to advance understanding of cities as complex human settlement systems (Alberti, 2016). Cities across the globe exhibit unique patterns, reflecting diverse socio-economic and biophysical characteristics, as well as their history and stage of development (Bai, 2003). The conventional, underlying mechanisms and universal laws of the urban system hardly function with the dynamic urban systems and people's behavior.

One of the primary reasons for the complexity is complex interactions among multiple heterogeneous residents and components across multiple scales. As many, diverse people migrate into cities, city dwellers' socio-demographic characteristics become complex. Consequentially, their demands on urban services and infrastructure and their social dynamic become complex. Further, their decisions are also highly heterogeneous (Waddell, 2013). These decisions are influenced by their diverse characteristics, perceptions, and preferences and directly and indirectly affect the urban system (Polsky et al., 2014).

One of difficulties that urban planners and policy makers experience is the lack of the data that represents the features of the individual resident. In general, the data available for policy makers and urban planners is aggregated into a relatively large geographical area such as neighborhood, city, or county. Therfore it is hard for them to have a good understanding on residents' demands and concerns occurred at micro-geographical areas. Residents' socio-demographic data is hardly available at the individual level or even at the micro-geographical level. In the U.S., for example, much socio-demographic data is typically available by census tract and/or traffic analysis zone (TAZ), which generally encompasses a population between 2,500 to 8,000 people (U.S. Census, 1994). In some cases, although exhaustive individual data are available, they are excluded from the public domain due to privacy reasons. For this reason, many planners and scholars have attempted to identify the micro-dynamics of socio-demographic features in a city or region. The purposes of the attempts are to understand persons' population attributes and the spatial location at the individual level.

The synthetic population is an example of individual population attributes. A synthetic population is a simplified microscopic representation of the actual population (Beckman et al., 1996). Although all the population attributes are not included, it represents microscopic details of the population since the synthetic population matches various statistical distributions of the actual population (Guo and Bhat, 2007; Lenormanda and Deffuant, 2013). In general, the goal of the synthetic population is to estimate the population attributes of both individuals and their organizations in households. While the synthetic population achieved the reliability of the estimated microscopic attributes of the population, the identification of each individual's accurate residential location remains at an early stage. Persons' locational data can be the best source of various urban planning practices, from understanding travel behavior and urban development patterns to uncovering the mechanisms that determine the dynamics of urban ecosystem services. For this reason, a group of scholars interconnects the synthetic population with large scale survey data such as the National Household Travel Survey (NHTS) data (Mohammadian and Zhang, 2008). However, due to the high cost and time-consuming data processing, it is hard to collect the data as frequently as needed and as completely as possible. Dasymetric mapping is a popular technique that allows allocating aggregated census population counts to likely habitable land uses.

Dasymetric mapping is a geospatial technique to more accurately distribute data that has been assigned to arbitrary boundaries, such as census blocks, using additional information such as land cover, but it relies upon the assumption of uniform population density since it still estimates populations at an area-scale (Michanowicz et al., 2019). Some studies report the approach that allocates aggregated population data into a smaller geographical unit such as census block, urban block, or property parcel (Michanowicz et al., 2019; Kim, 2012; Kim, 2010). The studies disaggregate U.S. Census populations by allocating an average person per household to geospatially-identified residential housing units after sorting out residential properties cross-referencing multiple datasets such as zoning, land-use, and property parcel. Employing address as the primary locational information, the studies typically attempted to allocate populations to residential parcels. However, the accuracy of the allocation remains unconfirmed.

Furthermore, this allocation method is not practical in many Asian countries like Korea, while being applicable to cities in the U.S., prelimarily dominated by singl family residential parcels (Kim et al., 2012). In general, sing family residential parcel typically refers a small, individual property occupied by one dwelling building. Unlike the U.S. cities, however, it is common for multiple buildings to be placed in a large residential parcel in Asian cities (e.g., large condominium complexes). Therefore, population being allocated to large multi-family residential parcels hardly represents local dyanmics of the residents. Therefore, parcl is not an ideal unit of allocation in Asian cities.

The purpose of this paper is to explore the methodology that allocates population data to a geographical unit at a micro-level. Unlike much previous research that attempted to allocate population data to a parcel level, this paper demonstrates the allocation of the population to a building level. Taking the City of Jeonju, Korea, as its study area, this paper attempted to allocate population data stored in a grid layer (100 meters by 100 meters) into a building footprint layer that represents the appearance of physical buildings. In order to achieve this goal, this paper classifies grid cells into five prototypical patterns based on the composition of residential building types in a grid cell. Then, it develops a population allocation method for each prototype of the grid cell.

II. Study Context

The geographical context of this paper is the City of Jeonju, Korea. Jeonju is a major city located in Jullabook-Do (Figure 1). Jeonju is a basin surrounded by mountains and has an area of 206.22km^2 and a population of 651,744 as of 2016. In particular, Jeonju city has an urban and rural complex structure. They are appropriately located in the center of the city. In Korea, more than 70% of the entire country is composed of mountainous areas, and cities and rural areas are formed in the remaining areas. The geopolitical characteristics of Jeonju have both urban and rural types in Korea, and there is an opportunity for representativeness appropriate to analyze the characteristics of land use and population activities. In addition, Jeonju has an incentive for the population and tourism industry as it contains the representative traditional architecture area of Korea called the Hanok Village. Based on these characteristics of population incentives, it is highly probable as a target site for various simulations of urban socio-economic activities. In particular, the headquarter of the Korea Land and Geospatial Informatix (LX) Corporation, which deals with spatial information as to its primary business model, moved to Jeonju, various active research activities are undergoing. For example, various mutual agreements have been made with Jeonju to solve social problems using digital twin technology among the 4th industrial revolution technologies.

For the core simulation function of digital twin technologies, it is essential to allocate the population information to the digitalized buildings located in an area. Based on the current location of LX and available data that can be collected from Jeonju, we establish primary data from individual activities for solving various social problems, targeting on Jeonju.

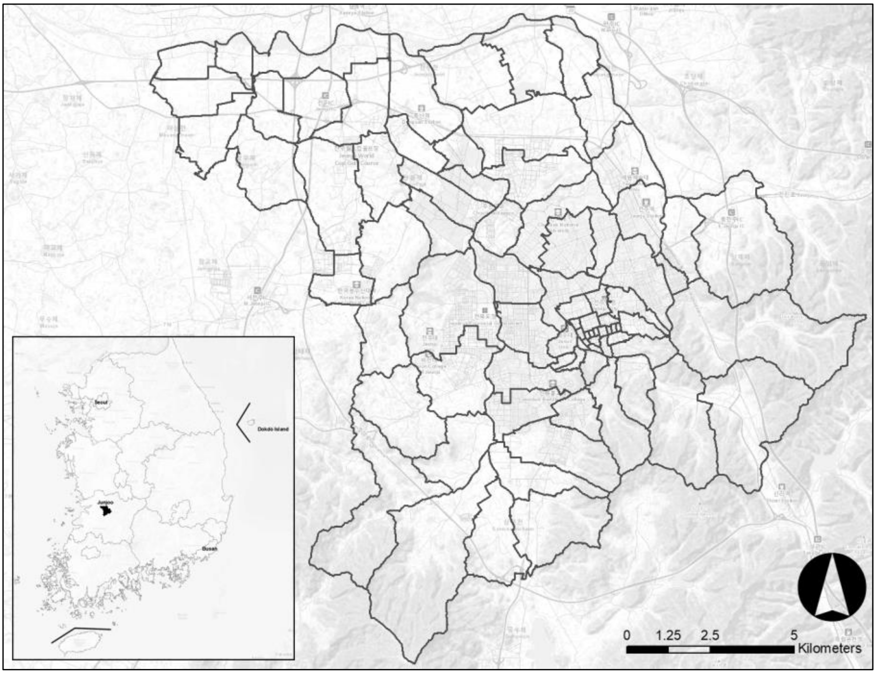


Figure 1 The Study Area: Jeonju-city, Korea

III. Data

The primary datasets for this study can be classified into two distinct categories that represent the population and physical urban space. This paper collected two datasets for the population. The first population dataset is the population data from Statistics Korea. This data is Korean census data, which is the most reliable population data source in Korea. However, since the data is aggregated by the administrative boundary called "Dong," the geographical extent of the data is too big to be employed for population allocation to buildings. Dong is comparable to census tract in the U.S. For example, the average area of the census Tracts in the city of Los Angeles is 1.34 square kilometers, while the average area of Dongs in the City of Jeonju is about 2.46 square kilometers. For this reason, this data set was only utilized for the purpose of confirmation and validation of the allocated data at the macro level. The population dataset used for population allocation was the population data collected from National Plan Policy Indicators.

The National Plan Policy Indicators provide population, buildings, land, and national land indicators using the National Territory Information Platform site[1] operated by the National Geographic Information Institute based on a statistical grid map for policy establishment. For the population data, which is the basis for this analysis, we could collect the data at the administrative district and grid units. Unlike the population data from Statistics Korea, the geographical unit of this data is a gird cell whose size is 100 meters by 100 meters. This micro-level population data allows scaling down population data to the individual building level.

The data representing physical urban space includes property parcel and physical building data. While the property parcel data delineates the legal boundary of a property, the building data includes not only the footprint of physical buildings, but also other attributes including address, zoning codes, and use classifications. These datasets were collected from the National Spatial Data Infrastructure Portal. National Spatial Data Infrastructure Portal collects data related to spatial information at the national level, such as digital topographic maps, including physical building data and cadastral maps, including parcel data, and It provides it in the form of an open market.

IV. The Typology of Population Grids

Prior to the population allocation, this paper removed building footprints that resided in non-residential parcels such as commercial, industrial, or institutional parcels. Then, the first step of the population data allocation into each building footprint is to classify the population grid into five types based on the building types within each grid (see Figure 2). Since the paper develops and applies a unique allocation method to each grid type, it is important to identify the typologies prior to the allocation. The process of the grid classification starts with a spatial analysis applied to single-family buildings and parcels. It was observed that there were multiple buildings in one single-family property. It is common that other buildings than a residential building such as barn and storage exist in a single-family property, especially in rural areas. In order to allocate population to only residential buildings, this paper screened out only one residential building per each single-family parcel. This process was depended on the visual observation that compares the building footprint with aerial photography. This allows identifying residential buildings in single-family properties. Additionally, this paper clearly identified low-density and high-

1 http://map.ngii.go.kr/ms/map/NlipMap.do?tabGb=statsMap

density multi-family buildings by querying the zoning code in the attribute of the building footprint data.

It was possible to classify the population grid into five types by spatially associating the building footprint with the population grid. They include

- Type 1: Only one building exists in a grid cell
- Type 2: Multiple buildings exist in a grid cell, but all of them are single-family residential buildings
- Type 3: Multiple buildings exist in a grid cell, but all of them are either low-density multi-family residential buildings or high-density multi-family residential buildings
- Type 4: Multiple buildings exist in a grid cell and they are mix with low-density and high-density multi-family residential buildings and
- Type 5: Multiple buildings exist in a grid cell and they are mix with three different types of residential buildings.

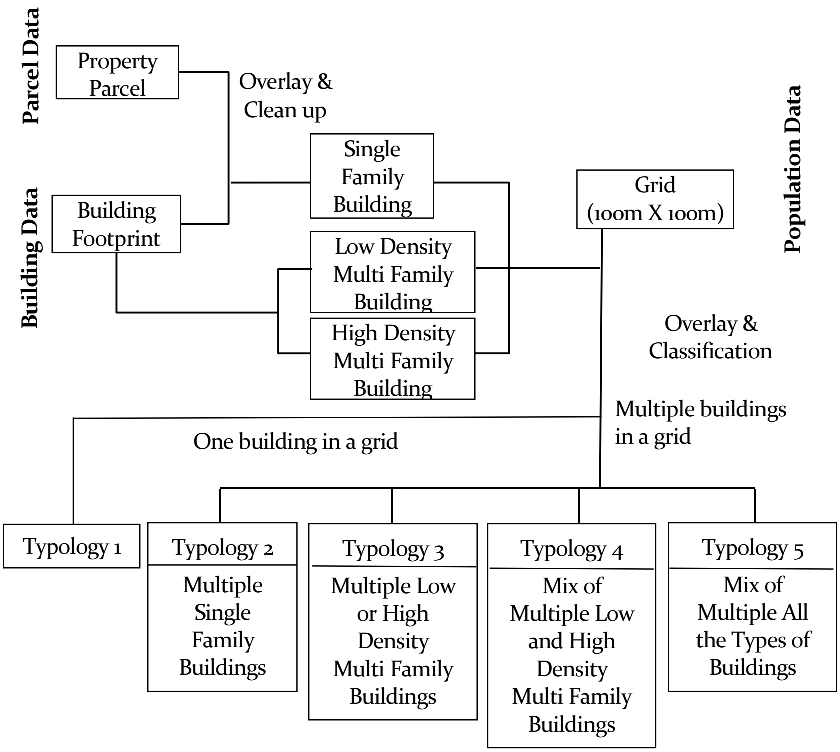


Figure 2 Flowchart of the Identification of Grid Typologies

V. Population Allocation by Each Typology

After the typology of the population grid was identified, this paper treated each grid type individually and applied a distinct mathematical formula to each type of typology. In the case of Type 1, the allocation is straightforward. Since there is only one building in a grid cell, the entire population of the gird cell was automatically allocated to the building. Thus, the population per building of Type 1 can be expressed using the following formula.

$$POPj = POPg$$

Where POPj = the population of building j
POPg = the total population of a grid cell

Type 2 refers to a case that although there are multiple buildings in a grid cell, the type of the buildings is consistent and they are single-family residential buildings. Thus, it is logical to evenly allocate the population of a grid cell to the buildings in the grid cell by dividing the population of a grid cell by the number of buildings in the cell, where we assumed that one household resides in a building regardless of the size of the building. This method can be expressed using the following formula.

$$POP_j = \frac{POP_g}{BLDG_c}$$

Where POPj = the population of building j
POPg = the total population of a grid cell
BLDGc = the number of buildings in a grid cell

After this allocation is finished, this paper computes the average value of the population per single-family residential building by Dong ($AVGPOP_{sf}$). While the average value represents a generic estimation of population per single-family residential building in the study area, it also reflects the local variations of the population since it is aggregated to each Dong. The average value will be used for the calculation of Type 5.

Type 3 is a similar case to Type 2. Unlike Type 2, Type 3 refers to a case that the type of residential buildings in a grid cell is consistently multi-family residential buildings, either low-density residential buildings or high-density residential buildings. Therefore, the method of even allocation adopted for Type 2 is also applicable to Type 3 since there is only one type of residential buildings in a grid cell. Unlike a single-family residential building, however, multiple households live in a multi-family residential building. Therefore, it is logical to hypothesize that the number of residents positively correlates with the size of buildings. Based on the hypothesis, the population of a grid cell is divided by the total building area rather than the number of buildings. The allocation method of Type 3 can be expressed using the following formula.

$$POP_j = POP_g \times \frac{BLDG_j}{BLDG_T}$$

Where POPj = the population of building j
POPg = the total population of a grid cell
BLDGj = the area of building j (square meters)
BLDGT = the total area of buildings in a grid cell (square meters)

In the same vein as Type 2, this paper computes the average values of population per low-density ($AVGPOP_{lmf}$) and high-density ($AVGPOP_{hmf}$) multi-family residential buildings by Dong after completing the Type 3 allocation. The average values represent the average number of people per 100 square meters of low-density and high-density multi-family residential buildings.

Type 4 is one of the common residential patterns in the study area. This type represents the areas where both low-density and high-density multi-family residential buildings coexist. For the allocation of Type 4, the average values computed in Type 3, $AVGPOP_{lmf}$ and $AVGPOP_{hmf}$, are utilized. This paper initiates the allocation by assigning an $AVGPOP_{lmf}$ or $AVGPOP_{hmf}$ value to each individual low-density or high-density multi-family residential building, respectively. Then, this paper computes the sum of the assigned population by grid cell and measures the difference between the sum and the total population of the grid cell. Finally, this paper adjusts the population assigned to each building by applying the ratio of the difference. For example, let's assume that the sum of the assigned population is 900 after applying the average population per low-density and high-density multi-family residential building to all the buildings in a grid cell. If the total population of the grid cell is 1,000, then there is 10 percent difference between the assigned population and the total of the grid cell. Thus, the final population per building is calculated by increasing the assigned population by 10 percent. The allocation method of Type 4 can be expressed using the following formula.

$$POP_j = \frac{Bldg_j \times AVGPOP_{lmf}}{100} \times \frac{POP_a}{POP_g}$$
$$if\ \ low - density\ \ multifamily\ \ resiential\ \ builing$$

$$POP_j = \frac{Bldg_j \times AVGPOP_{hmf}}{100} \times \frac{POP_a}{POP_g}$$
$$if\ \ high - density\ \ multifamily\ \ resiential\ \ builing$$

Where POPj = the population of building j
POPg = the total population of a grid cell
POPa = the total assigned $AVGPOP_{lmf}$ and $AVGPOP_{hmf}$ of a grid cell
BLDGj = the area of building j (square meters)
$AVGPOP_{lmf}$ = the average population per low-density multi-family residential building of a grid cell
$AVGPOP_{hmf}$ = the average population per high-density multi-family residential building of a grid cell

Lastly, Type 5 is the most complex mix of residential buildings, but this is a type commonly found. Since Type 5 is a combination of Type 2 and 4, the method of population allocation for Type 5 is similar to the methods adopted for Type 2 and 4. First, this paper assigns $AVGPOP_{sf}$ to each single-family residential building. Then, this paper computes the difference between the sum of the assigned $AVGPOP_{sf}$ and the total population of a grid cell. The difference indicates the number of people who live in multi-family residential buildings. Thus, the difference is allocated to multi-family residential buildings employing the method used for the allocation of Type 4. This method can be expressed using the following formula.

$$POP_j = AVGPOP_{sf}\ \ \ if\ \ single - family\ \ resiential\ \ builing$$

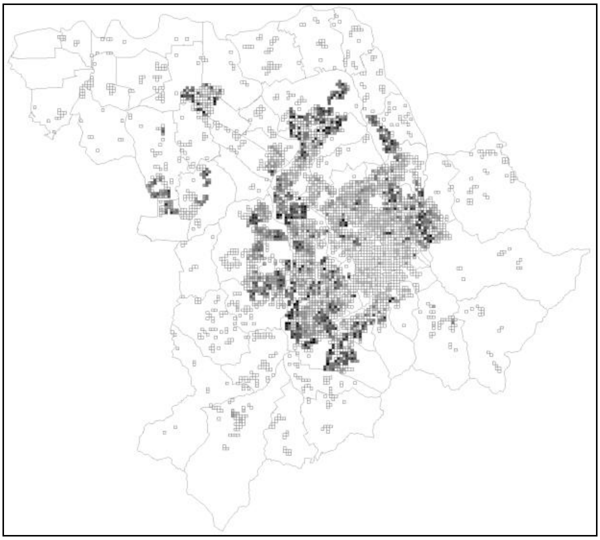
$$POP_j = \frac{Bldg_j \times AVGPOP_{lmf}}{100} \times \frac{POP_a}{POP_g - \sum AVGPOP_{sf}}$$
$$if\ \ low - density\ \ multifamily\ \ resiential\ \ builing$$

$$POP_j = \frac{Bldg_j \times AVGPOP_{hmf}}{100} \times \frac{POP_a}{POP_g - \sum AVGPOP_{sf}}$$
$$if\ \ high - density\ \ multifamily\ \ resiential\ \ builing$$

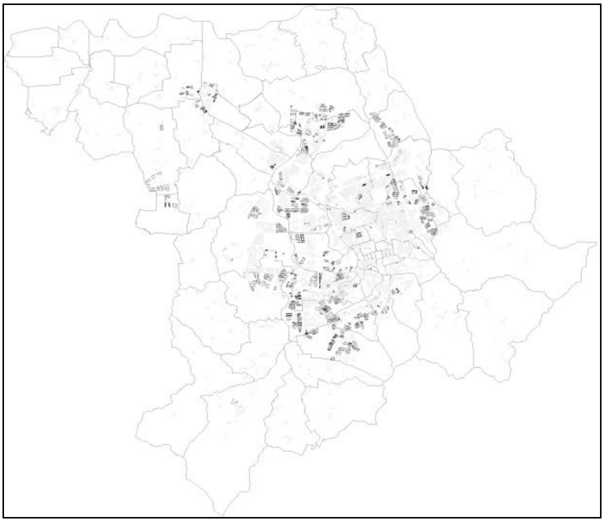
Where POPj = the population of building j
POPg = the total population of a grid cell
POPa = the total assigned $AVGPOP_{lmf}$ and $AVGPOP_{hmf}$ of a grid cell
BLDGj = the area of building j (square meters)
$AVGPOP_{sf}$ = the average population per single-family residential building of a grid cell
$AVGPOP_{lmf}$ = the average population per low-density multi-family residential building of a grid cell
$AVGPOP_{hmf}$ = the average population per high-density multi-family residential

building of a grid cell

The typology classification, followed by the population allocation per each type, allows successfully allocating the population values stored in the grid dataset to the building footprint dataset (Figure 3).



Population Distribution by a Grid Cell



Population Distribution by Residential Building

Low Medium High

Number of People

Figure 3 Before- and After-Comparison of Population Allocation

VI. Discussions

The number of residents in each residential building cannot be perfectly measured without conducting labor-intensive surveys or accessing sensitive private data. However, this study attempted to estimate the population with logical and reasonable steps on the building footprint only based on the secondary data sources such as building volume data and building use code data. Because the methods demonstrated in this paper used residentially-censored and publicly-available location data with a persons-per-building estimate from the residing grid cell, this is entirely different and opposed to an aggregate multi-county average and/or dasymetric mapping. This approach also differs from previous research that allocates populations to parcels. Since there are large number of condominium complexes consisted of multiple high-raised condominium buildings in the study area, our suggestion is innovative is especially meaningful for the areas that have high density. Indeed, it can improve the allocation accuracy of the complexes in comparison to the traditional methods that disaggregate populations to parcels. Another important contribution of this study to the regional and spatial systems is that the approach does not rely on the assumption of uniform spatial homogeneity of populations within an aerial unit. The results produced by this paper better represent residence in discrete buildings in the real world rather than continuously across space. Therefore, this paper accounts for the variations of residence in reality by applying multiple layers of criteria, including five residential typologies in a grid cell and three residential building types. This paper also overcomes the issue of potential temporal misalignment by employing the population data and building footprint data in the same year, 2016. We believe this approach could reach to develop a cornerstone to construct a spatial digital twin model for a city to be applied to simulate if a regional innovation system can be achieved in the target region or not.

However, the issue of misclassification was identified because the population allocation relies on the secondary datasets only from three different organizations. It is noteworthy that the discrepancy between building footprint and property parcel layers was observed in the study area, especially in rural areas. While the building footprint layer tends to capture physical domicile locations better, it does not align well with parcel boundaries. Therefore, this paper conducted intensive visual observations and analyses in order to match building footprints with the parcel that the footprints reside. It is also important to note that the allocated populations represent the static, nighttime residential population- based on information on where people sleep. There is recent research that captures the snapshot of people's trajectories and movements based on big data like cell-phone signals, credit card records, unmanned aerial vehicle (UAV), or social media (Kim, 2010; Kim and Chanchlani, 2018; Chandrasekar, 2015). Unlike the research, this paper underestimates the mobility of people, and the dynamic nature of populations in space and time. Nonetheless, the method proposed by this paper has its advantage in terms of the capability to build comprehensive, consistent, and longitudinal micro population data since it utilizes public data that has been regularly published a long period of time and covers the entire population in the county.

On the other hand, this paper does not demonstrate the validity of the allocated population. Since there is a lack of data that represents the actual number of residents in each building due to the privacy issue in Korea, it is hard to confirm the accuracy of the allocation. Water and electricity usage data per household can be a reasonable proxy data that can represent the number of residents in the household. Since the data is already attached to an individual address, it is also relatively easy to spatially tie to the building that the household resides. Therefore, it can be considered to validate the allocation employing the proxy data, even though it would be useful to compare our estimates with actual data.

VII. Conclusion

This paper proposed a systemic approach to disaggregate census population data into building footprints, which are the most acceptable geographical unit in terms of residential location. Employing population data stored in a grid layer, this paper explored the classification of five prototypical residential patterns in a grid cell and the mathematical formulas that allocate aggregated population values to the individual building footprint. This paper is an exemplary case that demonstrates the allocation of census population to discrete buildings accounting for variations and heterogeneity of population distribution in the real-world.

As urban phenomena become complicated, urban scientists and planners have introduced advanced mathematical and economic models, which are applicable to the exploration of urban systems and the discovery of new insights for planning and policy decision-making. These models tend to run with large datasets that not only cover extended geographical areas, but also represent the details of sophisticated dynamics at the local level. This paper demonstrated an approach to support the models by feeding the distribution of populations at the micro-level, achieving a data-based system innovation.

It is noteworthy to carefully condsider urban built environment when selecting a disaggregation method of population. Much of previous research reports the methods that allocate population data to proprety parcel and that were primarily developed based on the case of U.S. cities. Thus, the adoptability of the methods to Asian cities remains questionable since the structure of urban environment and land use systems in Asian cities differ from ones in U.S. cities. Thus, it is important for urban planners and scholars in Asian countries to develop customized disaggregation methods that fit with their cities.

With the emergence of big data and data analytics technologies, the volume and diversity of urban data are increasing rapidly. The influx of new data and analysis methods will become faster and richer due to the digitalization of administrative and operational records, and the proliferation of urban sensors and Internet-of-Things technologies. It is plausible to envision that the technologies will allow collecting and identifying the population attributes of persons at the individual level. Therefore, it is important for scholars working in the urban system to proactively link emerging technologies to conventional datasets like census data. By doing so, it will be possibly identify innovative methods that create a population distribution dataset representing the comprehensive and dynamic nature of population at the micro geographical level and combine it with our real life.

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