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Abstract When comparing accessibility, the interpretation of results is complex because of lack of standard or universal norm. This uncertainty issue of the distinction from the lack of standard can be solved using the multi-level approach of fuzzy set: universal, relative, and absolute index. Since a fuzzy set approach deals with the vagueness and indiscernibility of accessibility index, the proposed approach suggests a better solution to classify the index than a crisp set or even a single-level fuzzy set approach. In this study, we evaluate job accessibility of locations in the Columbus MSA in Ohio, USA for 18 worker groups. The uncertain distinction between strong/weak, rich/poor, and higher/lower accessibility is improved by the multi-level approach. Moreover, this study attempts to enhance our understanding of spatial structure of job accessibility disaggregated by occupation type and gender.

Keywords Employment structure · Job accessibility · Disaggregate · Fuzzy set membership · Uncertainty

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Introduction

Urban size and structure play an important role in people's lives. The migration of different types of employment from central cities to suburbs and edge cities (Garreau 1991) may bear serious implications for general patterns of metropolitan land-use and commuting patterns, and will affect the spatial expression of gender, and other demographic differences. Although 63 % of metropolitan jobs was still concentrated in central cities (Mieszkowski and Mills 1993), urban employment structure has been dramatically changed ever since suburbanization has emerged. These changes include the location of jobs and the types of job embedded on the location. For example, urban employment structure has been changed from centers of production to centers of information processing since 1960 (Kasarda 1989). During the process, many blue-collar jobs have either vanished or moved from the core areas of cities, replaced by knowledge-intensive white-collar jobs. In particular, labor markets for lower-skilled service jobs along with goods-processing industries have been weakened, while managerial, professional, and high-level technical and administrative support jobs have increased in central cities. Likewise, the employment structure embedded on gender has been changed along with the process of job suburbanization. For instance, "pink-collar ghettoes" were identified with different sets of employment opportunities and wage levels for women and men (England 1993; Hanson and Pratt 1991).

As those studies imply, workers are not homogeneous group, and that differences among them must be carefully uncovered. Refining our understanding of the spatial situation that different groups of workers face is an important extension of earlier work on the geography of employment. In this study, we use a fuzzy set approach to evaluate the differences between location and worker groups using job accessibility. The job accessibility is measured at tract level for worker groups from the destination perspective. Since accessibility in this study is the characteristics of both a location and a group of people, the use of fuzzy set clarifies the interpretation of job accessibility by identifying the spatial and social heterogeneity in various ways. Job accessibility can be defined as the potential of job opportunities. Job accessibility measured at workplace (supply side) enhances our understanding of the spatial patterns of employment opportunities disaggregated by gender and occupation type. This study reveals the heterogeneity of the employment situation by differentiating jobs by gender and occupation type. The 9 occupational groups for men and 9 for women make the 18 representative groups of workers as is in Table 1. The different level of employment opportunities for each group characterizes each tract, helping us learn whether the Columbus MSA has gendered scheme in regard to job accessibility.

The purpose of this paper is (Aerts et al. 2003) to identify job centers of worker groups by gender and occupation, and (Ahlqvist 2005) to compare the geographical and gender differences of job accessibility for each occupational category. In particular, we utilize a multi-level approach of a fuzzy set (Benz et al. 2004; Chen and Huang 2008; Ladner et al. 2003) to discuss the uncertainty issue of comparing job accessibility by gender and space for each occupation.

Table 1 Occupational classification systems

Aggregate occupational groups (9 categories)	CTPP 2000 classification (24 groups)
1. Mangers	1. Management
	2. Farmers and farm managers
2. Professionals	3. Business and financial operations specialists
	4. Computer and mathematical
	5. Architecture and engineering
	6. Life, physical, and social science
	7. Community and social service
	8. Legal
	9. Education, training
	10. Arts, design, entertainment, sports, and media
3. Healthcare and technicians	11. Healthcare practitioners and technicians
4. Services	13. Protective service
	14. Food preparation and serving related
	15. Building, grounds cleaning, maintenance
	16. Personal care and service
5. Sales workers	17. Sales and related occupations
6. Administration and healthcare support	12. Healthcare support
	18. Office and administrative support
7. Farming, fishing, and forestry	19. Farming, fishing, and forestry
8. Transportation and production	20. Construction and excavation
	21. Installation, maintenance, repair
	22. Production
	23. Transportation and material moving
9. Military	24. Armed forces

This paper is organized as follows. The following section explores issues relevant to an examination of the urban structure and job accessibility and relates analyses shown in previous research. The methodology part provides a brief explanation of job accessibility measurement as well as the characteristics of fuzzy set membership function (MF). Our approach uses the empirical analyses of the Columbus MSA in Ohio, in which a disaggregate approach is adopted to split the aggregated commuting flow of Part 3 in the Census for Transportation Planning Package (CTPP) data. The destination-specific accessibility measured from the empirical analysis is the major data source in this study. Concluding remarks are given in the final section.

Urban spatial structure and accessibility

Cities have been spreading out in recent decades with the decentralization of population and employment forming polycentric urban structures. These changes are more pronounced and rapid in the American context. The classic representation of cities has concentric structure around one center with employment density gradients declined with increasing distance from the central city (Mills and Tan 1980). This monocentric entity shows that cities' central business districts (CBDs) tend to have more jobs than housing, which leads higher rent prices owing to higher job accessibility at the center (Alonso 1964). However, the monocentric models have lost much of their explanation power for contemporary urban settings (Clark 2000) given the emergence of polycentric urban form characterized by decentralized employment centers and sub-centers operating on the fringes of cities (Kwan and Weber 2003).

The decentralization process of population and employment is complex and not easily characterized even in the USA. Some scholars have tried to understand urban form in relation to the economic shift from manufacturing basis toward service industries and office employment (Armstrong 1979; Clark 1982). Other researchers (Cervero 1996; Peng 1997) concerned more on land use and its relation to commuting. The location imbalance of jobs and workers and its influence on commuting are well discussed in the jobs-housing balance studies (Cervero 1989a, b, 1996; Peng 1997), while excess commuting are mainly focused on the relationship between urban structure and average commuting distance (Hamilton 1982; White 1988). Those concerns on both people and location are well incorporated in accessibility because accessibility itself is at least as much about people as places (Farrington 2007). For example, a person's level of access to a job can either be explained by personal or (and) locational access to available transportation mode, road network, job-related skill, educational level, distance to job, number of jobs available, etc.

As a key indicator of land use, transportation planning, and urban policy, job accessibility relates labor market status of people to their geographical proximity to available jobs. Using a gravity-based model, job accessibility has been used to capture advantage of job access by group of people such as job competition (Wang 2001) and wage-groups (Wang 2003). Moreover, accessibility is used to evaluate the potential for interaction in geographic space controlling for the internal structure of the city. In this sense it can inform analyses of suburban sprawl and decentralization (Lucy and Phillips 1997), edge city development (Garreau 1991), poly centricity (Horner 2004) and other configurational issues influencing commuting and congestion. Gao et al. (2008) used the structural equation modeling to examine the connections between job accessibility, workers per capita, income per capita, and autos per capita at the aggregate level with year 2000 census tract data.

A conventional accessibility measure can be described using a number of opportunities at destinations and spatial impedances between origins and destinations (Hansen 1959). In this approach, boundary areas far from the job-rich areas have less job accessibility than most accessible employment centers. Cervero et al. (1999) demonstrated that residents who were low income in inner-city had serious job accessibility problems. Likewise, spatial mismatch studies have been addressed in diverse spatial settings using accessibility index. Parolin and Kamara (2003) examined changes in accessibility to employment by public transport in Sydney from 1981 to 1996. In their study, the inner-city areas had increased accessibility with rich public transport while areas beyond 20 km had decreased accessibility due to the poor public transport. Lau and Chiu (2004) showed uniqueness of Hong Kong in regard to accessibility between jobs and housing. Due to its dynamic economic growth and high efficiency of transportation system, low income employees have higher accessibility than workers in other cities in Europe and the US. They concluded that Hong Kong has reasonable travel time between jobs and housing and is not affected by trade-off between accessibility and living costs because of a compact city structure and high efficiency government.

A gravity-based index of spatial interaction (SI) model is well incorporated into the job accessibility, where more distant jobs are weighted less influential. In this way, the effect of one location on another is directly proportional to its attraction and is inversely proportional to its distance. The distance decay function is usually assumed to be an exponential or a power function. According to Fotheringham and O'Kelly (1989), exponential function is more appropriate than power function for analyzing short distance interactions such as those that take place within an urban area while the power function is generally held to be more appropriate for analyzing longer distance interaction such as migration flows. By generalized function of distance, the strength of relationships between locations diminishes as separation increases (Goodchild 2006). When a generalized powered exponential distance function is incorporated into the accessibility model, accessibility at location i is as follow:

$$A_i = \sum_{j=1}^{n} W_j \exp(-\beta \cdot d_{ij}) \quad (1)$$

where A_i accessibility of zone i to all j, W_j opportunities at zone j, d_{ij} spatial impedance between zone i and j, β distance decay parameter ($\beta \geq 0$).

Accessibility can be analyzed as a universal or a relative concept of accessibility. However, interpretations of results need careful guidelines. When job accessibility is used as a relative measure for comparison, it can evaluate the locations or the different groups of worker. The differences between groups are focused especially when social equity issue arises while the difference between locations is used to improve spatial condition or removing spatial barriers. In both cases, a relatively 'poor (or low)' accessibility is an important issue to discuss. As Farrington (2007) pointed out, accessibility has not been decided as either a concept of universal or relative concept. Therefore, the interpretation of accessibility needs to be based on various circumstances of the area, people, and measure. Setting a universal standard is helpful to identify the locations of group(s) of lower/higher when accessibility is used in planning area when their goal is to meet the universal norm.

In this paper, we deal with the multi-level fuzzy set approach and the concept of a job center which has been dealt with in few of existing works. There have been existing works analyzing the accessibility using fuzzy set approaches where a membership represents a degree rather than a binary value. Heikkila (2000) provided a ground work to combine the fuzzy logic (Zadeh 1965) and the club theory (Buchanan 1965) to model accessibility. Oh and Jeong (2002) evaluated urban residential environment including accessibility to amenities using GIS and fuzzy set approach. Their work demonstrated that the fuzzy approach was useful to estimate the accessibility. Thériault et al. (2004) measured and analyzed subjective perception of accessibility using fuzzy logic criteria to model accessibility to urban services. They found that the fuzzy logic brought insight in understanding commuting patterns and individual's travel behavior. Pieczyński and Robak (2008) measured a service accessibility using fuzzy methods to assess non-technical service aspects that may have fuzzy quality by their nature. The fuzzy set approach has also been developed to a multi-level to classify an image of urban area at different scales with hierarchical dependency (Benz et al. 2004). Chen and Huang (2008) showed that general knowledge of the concept can be discovered with multi-level approach. An uncertain concept with hierarchy was modeled by multi-level fuzzy sets to provide a continuous gradation of meaning in spatial data mining (Ladner et al. 2003).

Methodology and data

This study tries to reveal and deal with ambiguity in defining and comparing job centers for different worker groups using job accessibility. We used two major methodologies for the evaluation and comparison reasons: job accessibility and multi-level approach of fuzzy set. In our study, job accessibility refers to the ease of attracting workers as an employer. Firms (office, shops, etc.) that are in places of high job accessibility can attract many more workers within a shorter distance range, while companies in low accessibility area can attract a lot less workers within the same distance range. The job accessibility used in our study is related to distance decay and cumulative number of workers who comes into the area for a job. In addition, the job accessibility itself is disaggregated by workers' occupation and gender. Using 2000 Census Transportation Planning Package (CTPP) where O_i^{kg} and D_j^{kg} for each gender (g) and occupational category (k) are available in the CTPP Part 1 and Part 2 data, a SI model is applied to predict disaggregate zonal flows (T_{ij}^{kg}) for each gender (g) and occupation (k) group as follow:

$$T_{ij}^{kg} = A_i^{kg} O_i^{kg} B_j^{kg} D_j^{kg} \exp(-\beta^{kg} c_{ij}) \tag{2}$$

$$A_i^{kg} = \frac{1}{\sum_j B_j^{kg} D_j^{kg} \exp(-\beta^{kg} c_{ij})} \tag{3}$$

$$B_j^{kg} = \frac{1}{\sum_i A_i^{kg} O_i^{kg} \exp(-\beta^{kg} c_{ij})} \tag{4}$$

where A_i^{kg} and B_j^{kg} ensure that

$$\sum_j T_{ij}^{kg} = O_i^{kg} \quad \forall i \tag{5}$$

$$\sum_i T_{ij}^{kg} = D_i^{kg} \quad \forall j, \tag{6}$$

respectively.

Where kg occupation (k) and gender (g) combination which ensures ($\sum_{kg} T_{ij}^{kg} = T_{ij}$) for all i and j, $\sum_{kg} T_{ij}^{kg}$ estimated number of commuters between i and j for kg group, T_{ij} aggregate number of commuters between i and j observed in CTPP Part 3 without disaggregating by k and g.

Job accessibility index used in this study is extended from a conventional accessibility model (Hansen 1959) in a way to incorporate the detailed OD flow matrix of 18 groups shown in the model above. The job accessibility for occupation k and gender g (ACC_j^{kg}) measured at destination location j can be defined as follow:

$$ACC_j^{kg} = \sum_i^n A_i^{kg} O_i^{kg} \exp(-\beta^{kg} \cdot d_{ij}) \tag{7}$$

where ACC_j^{kg} job accessibility at zone j for occupation k and gender g, A_i^{kg} modeled no of workers at location i for occupation k and gender g, O_i^{kg} census no of workers at location i for occupation k and gender g, d_{ij} spatial impedance between zone i and j, β^{kg} distance decay parameter for occupation k and gender g ($\beta \geq 0$).

In particular, the O_i^{kg} $exp(-\beta^{kg} d_{ij})$ part represents the distance decay of no of workers for occupation k and gender g at location i following exponential function of distance between i and j (See "Appendix 3" for more details about the model). As one of the key methodological components of this study, job accessibility is calculated using a detailed OD flow matrix and is used as tools for understanding the locational characteristic of each worker group. Since the accessibility score is influenced by distance which is mainly governed by the changing value of distance decay parameter (β), the calibration for β reflects different commuting behaviors of worker groups in a well-designed disaggregate model.

There exists uncertainty in defining job centers based on the accessibility measure due to the heterogeneity as mentioned in Introduction. In other words, no clear-cut boundary of job center exists. Its spatial boundary is rather continuous. This uncertainty can be reduced by defining the norm for both geographic locations and worker groups. Fuzzy set approach is utilized to capture the transition of the boundary in terms of space and concept (Ban and Ahlqvist 2008). Moreover, a vagueness of uncertain job center boundaries can be clarified by a partial membership of a fuzzy set (Zadeh 1965). The fuzzy set treats the continuous membership by assigning a value between 0 and 1. For example, when an area has higher degree of the job accessibility than a norm it has a larger membership value in the fuzzy set MF(s) than 0.5. A norm is defined as the sum of average and standard deviation for each worker group. When binary definition is used, tracts with higher accessibility than a group' norm have a membership value of 1. For continuous space, however, a "crossover point" is considered to place a transition zone so the crossover points of fuzzy sets lie at the boundaries of the corresponding Boolean set (Burrough and McDonnell 1998). In this way, an area could be classified as a different degree of job center. This so-called fuzzy set approach reveals greater heterogeneity of uncertain classification of job centers while dealing with vagueness (Fisher 1999) and uncertainty (Wilson 2001).

To have a better understanding of the heterogeneity of job accessibility for both locations and worker groups, we use three level variables to define the concept. In this multi-level approach, each level has different crossover points and fuzzy sets MF. It also has its different spatial patterns giving us different interpretations for each approach. Based on the disaggregate accessibility, our multi-level fuzzy set consists of (Aerts et al. 2003) an absolute index that considers 18 crossover points from 18 categories by occupation types and gender, (Ahlqvist 2005) a relative index that considers 9 crossover points from 9 categories by occupation types only, and (Alonso 1964) a universal index that considers only single crossover point from all 18 categories by occupation types and gender. Using these multi-level crossover points, we assigned three sets of fuzzy MFs for each tract (total 379 tracts). Each set has 18 groups of worker differentiated by their occupation and gender. On the crossover point a membership value of 0.5 means that the area is a job center with 50 % sure. Assigning a membership value between 0 and 1 that crosses over the membership value of 0.5, a simple linear fuzzy set MF gives each census tract the membership values of being job centers between 0 and 1. For example, fuzzy set MFs for the Managers (K1) occupation can be formulated as a formula (8) with the average accessibility of 568 and the standard deviation of 629:

$$MF_{(K1)} = \begin{cases} 0.00042 \cdot X & \text{for } X \leq 2,394 \\ 1 & \text{for } X > 2,394 \end{cases} \quad (8)$$

In the formula (8), the crossover point for the male K1 occupation is 1,197 (568 + 629). Thus, any tracts above 1,197 accessibility values will have membership values above 0.5. Since the fuzzy set membership value cannot exceed 1, a membership value of 1 is assigned to the tracts with higher accessibility than 2,394. In the same way, fuzzy set MFs for other occupation types are developed and used in our study.

The difficulties in interpreting comparisons within an occupation are overcome by the single approach. However, there are still complexities remained in comparing accessibility between occupational groups and between locations. There are several ways to address the uncertainty between the fuzzy sets. For instance, the entropy index shows the amount of information necessary to define the membership of a location. It also measures the distance between a membership value and the mean membership value of a location (Aerts et al. 2003). Measuring distances and areas overlaid between two fuzzy sets is addressed using a similarity and overlap metric by Ahlqvist (2005). A confusion index tests whether one or more membership values dominate(s) at a location. In other words, the confusion index (CI) in the formula (9) measures a ratio between the largest membership value and the second largest membership value for a location (Burrough et al. 1997, 2001).

$$CI = (\mu_{(\max-1)\mathrm{i}}/\mu_{(\max)\mathrm{i}}) \quad (9)$$

where $\mu_{(max)i}$, the membership value with the maximum value at location i, $\mu_{(max-1)i}$ the second largest membership value at the same location.

If $CI \to 0$, then one MF dominates at the location with little uncertainty. If $CI \to 1$, then there exists confusion between the MFs.

The entropy index (EI) represents the uncertainty of a random variable (Cover and Thomas 2006) as well as the level of spatial concentration and dispersion (Li and Yeh 2004). The higher entropy index means more uncertainty between the MFs of the location. The maximum value of the EI can exceed 1. It is defined by Shannon's entropy in the formula (10) (Shannon and Weaver 1962; Singh 1999).

$$EI = -\sum P_i \log_e(P_i) \quad (10)$$

where P_i a value of a MF i at each location.

The variance index (VI) shows the average of squared distance from one membership value to all other membership values at a location (McGrew and Monroe 2000) as detailed in formula (11) where X_i represents the membership value of a fuzzy set MF at a location, and $\overline{M}$ corresponds to the mean value among the all fuzzy set MFs at the location.

$$VI = \sum_{i=1}^{n} (X_i - \overline{M})^2 \quad 0 \leq X_i \leq 1, \quad \text{and} \quad 0 \leq \overline{M} \leq 1 \quad (11)$$

Based on these three indices, we measured the uncertainty of the job centers in urban-suburban membership values of the occupation types by gender, and represented the results as maps (see "Appendix 2"). As can be seen in "Appendix 2", each index represents how much the fuzzy sets based on the universal index are different or similar at each location. For example, darker gray areas mean that the fuzzy sets are much different (much uncertain), and lighter gray areas mean that they are much similar (less uncertain) at the locations. However, each index shows different degrees of the uncertainty from each other. For instance, the CI ("Appendix 2a, b") and the VI ("Appendix 2e, f") are more effective to show a gender difference than the EI ("Appendix2c, d"). On the other hand, the EI does a better job at representing heterogeneity of the uncertainty within the study area than the other two indices do. In addition, the VI shows a higher degree of heterogeneity for the surrounding counties than the CI does. Interestingly, the VI of female ("Appendix 2f") shows much higher levels of uncertainty than the VI of male ("Appendix 2e") does. In general, it would be important to choose a relevant uncertainty-measurement of fuzzy sets according to the purpose since the measurements could provide different outcomes.

Empirical results

The job accessibility was measured at employment locations trying to identify the concentration of jobs by counting number of workers who comes into the area (j). Base on the job accessibility formula (7), the job accessibility is high in areas where the location attracts more corresponding workers from the near locations. It is not homogeneous among locations and among worker groups. However, it is not easy to tell which occupation in which place has a better job accessibility than others. Such decisions should follow careful examinations and comparisons.

First of all, the differences between occupation and gender groups are explored using absolute index of 18 different crossover points. In this case, the locational variation is effectively shown. Figure 1 shows locational variation of the administration and healthcare support (K6) worker group throughout the study area ranging from 52 to 9,652. It depicts different degrees of attraction at destination j for K6 groups of men and women. K6 jobs are scattered across the region with several significant but minor suburban job centers. Generally, gender differences are not significant as spatial difference. However, workers in this occupation have different job accessibility at some tracts, especially at the outside of the urban (or suburban) centers. Spatial variations of job accessibility are well recognized within one group. The heterogeneity among tracts is well represented in the map where darker hue represents higher accessibility. However, the accessibility between genders is concealed due to lack of consensus between gender groups. Since K6 is a female dominant job group with a much higher accessibility for female compared to male counterpart, some differences between genders were expected. This lack of consensus between groups nullifies the difference between genders. Thus, the absolute index is only effective in showing spatial variations within groups.

Second of all, the relative index for job accessibility is applied with a shared crossover point between men and women. The greatest differences are found in transportation and production occupation (K8), showing a higher accessibility for men than women. In Fig. 2, the differences between K8 male and K8 female are well displayed at the tract level using this index. Many more job centers are found for K8 male workers with significantly higher (about three times) accessibility. Most tracts have gendered dimensions except a few job centers. The gendered job centers attract more men to the centers, characterizing the location as more "blue-collar" rather than gender neutral or "pink-collar" job center. Omnipresence of job centers for male is also well presented. However, spatial variations for female are concealed because the co-average between male and female is too high for the female K8 group masking the differences within the group. Female workers in Fig. 2b where darker hue has higher accessibility show less job centers and less spatial variations relative to male counterpart in Fig. 2a. Not only in K8 group but also other occupational groups have gender differences in terms of job accessibility. Many tracts have been identified as gendered dimensions holding lower accessibility for one gender relative to the counterpart depending on occupational type. The different degree of accessibility between male and female is well expressed by the relative

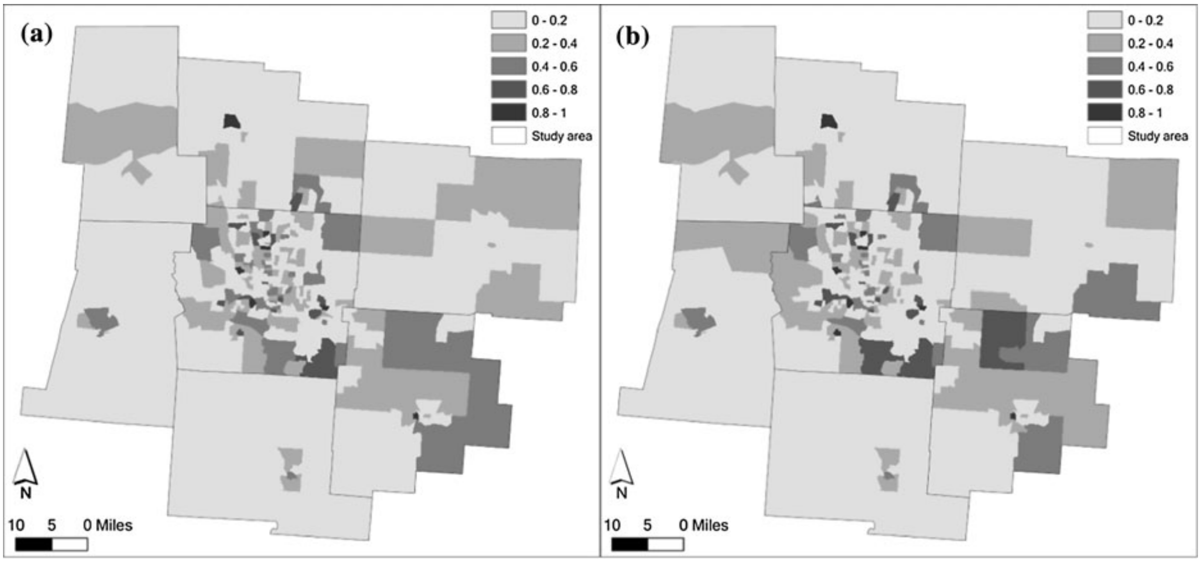


Fig. 1 Job accessibility using absolute index of administration and healthcare support (K6) job group by gender: **a** (Male) and **b** (Female)

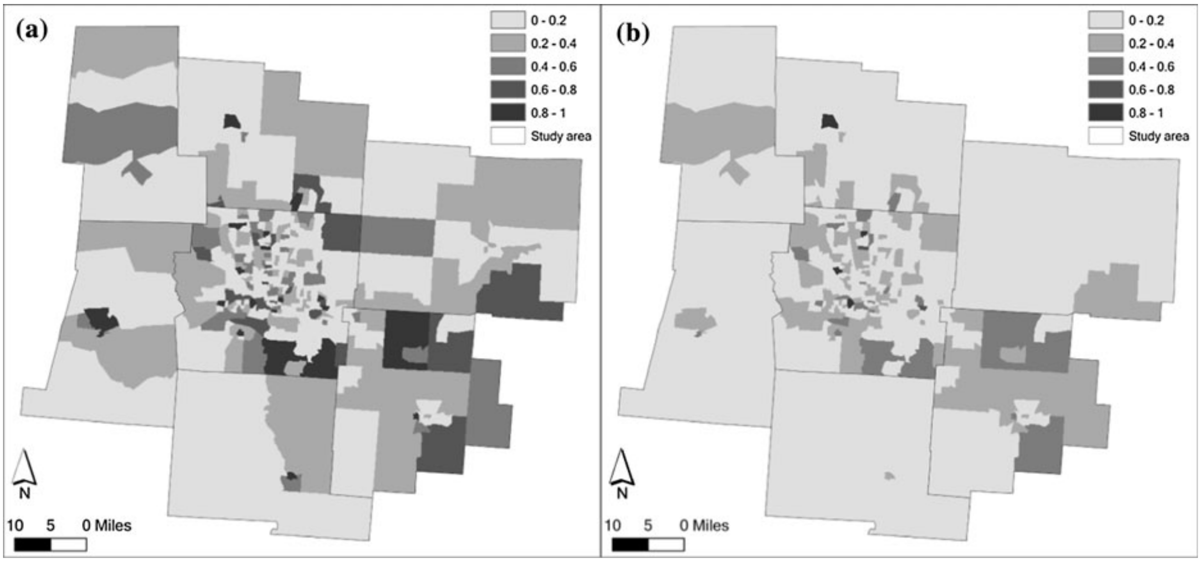


Fig. 2 Job accessibility using relative index of transportation and production (K8) job group by gender: **a** (Male) and **b** (Female)

index while moderately expressing the spatial differences for certain group.

Thirdly, the universal index is applied to see the compound differences by occupation, gender and location using single crossover point. As can be seen in Fig. 3, the map shows heterogeneity of job accessibility amongst worker groups as well as amongst 379 tracts. For example, jobs with low accessibility are easily identified for farming, fishing, and forestry job category (K7M, K7F) and military occupation (K9M, K9F). These occupational differences are well recognized along with gender differences with help of the universal index. The K6 and K8 groups show the best examples

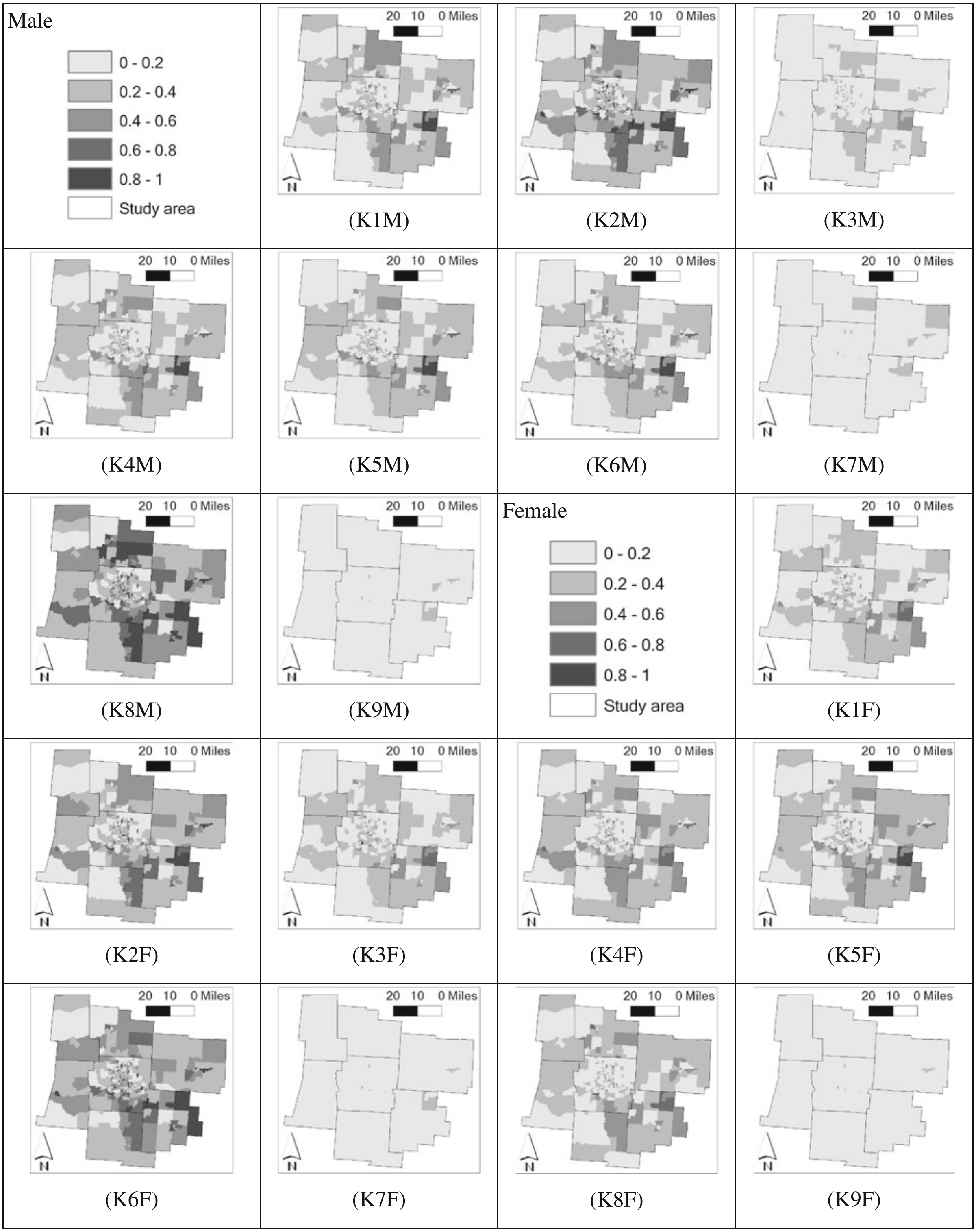


Fig. 3 Membership values of job centers in urban-suburban using universal index

Table 2 Three level index approaches with variation

Variation\index	Absolute	Relative	Universal
Spatial variation	High	Medium	Low
Group variation	Low	High	Medium
Compound variation	Low	Low	High

with greater gender differences. Spatial patterns compounded by both gender and occupation are well illustrated using the universal index. The crossover profiles for each group are also illustrated in "Appendix 1". Since the 18 groups have different job accessibility with different spatial patterns, such variations are reflected on the slopes of each MF profile. For example, the MFs of K8M and K8F show the gender difference while those of K4M and K4F display the gender similarity. Also the MFs of K5M and K9M illustrate the occupation type difference whereas those of K1F and K3F show the similarity of occupation type.

As summarized in Table 2, spatial variations are most effectively represented with the absolute index. The relative index turns out to be a better way to show group variations by either gender or occupational type than others. Compound variations mixed by both gender and occupation type are successfully identified with the universal index. Thus, the proposed approaches provided us the effective ways to reveal non-uniform patterns of the disaggregate job accessibility. Each approach has advantages and disadvantages in identifying the spatial variations in various ways. The absolute index is effective in showing spatial variations within groups, while least effective in making a distinction between genders or amongst occupational groups. For group variations (gender difference in this case), the relative index is the most effective method. It also demonstrates the different degree of job accessibility between genders or among occupational groups. However, the relative index is not the best for either occupation variations or spatial variations. The universal index found to be the best to illustrate spatial patterns of compounded group of both gender and occupation. Since our job accessibility is disaggregated by two characteristics and mixed each other, the universal index was effective to reveal variations between groups and locations.

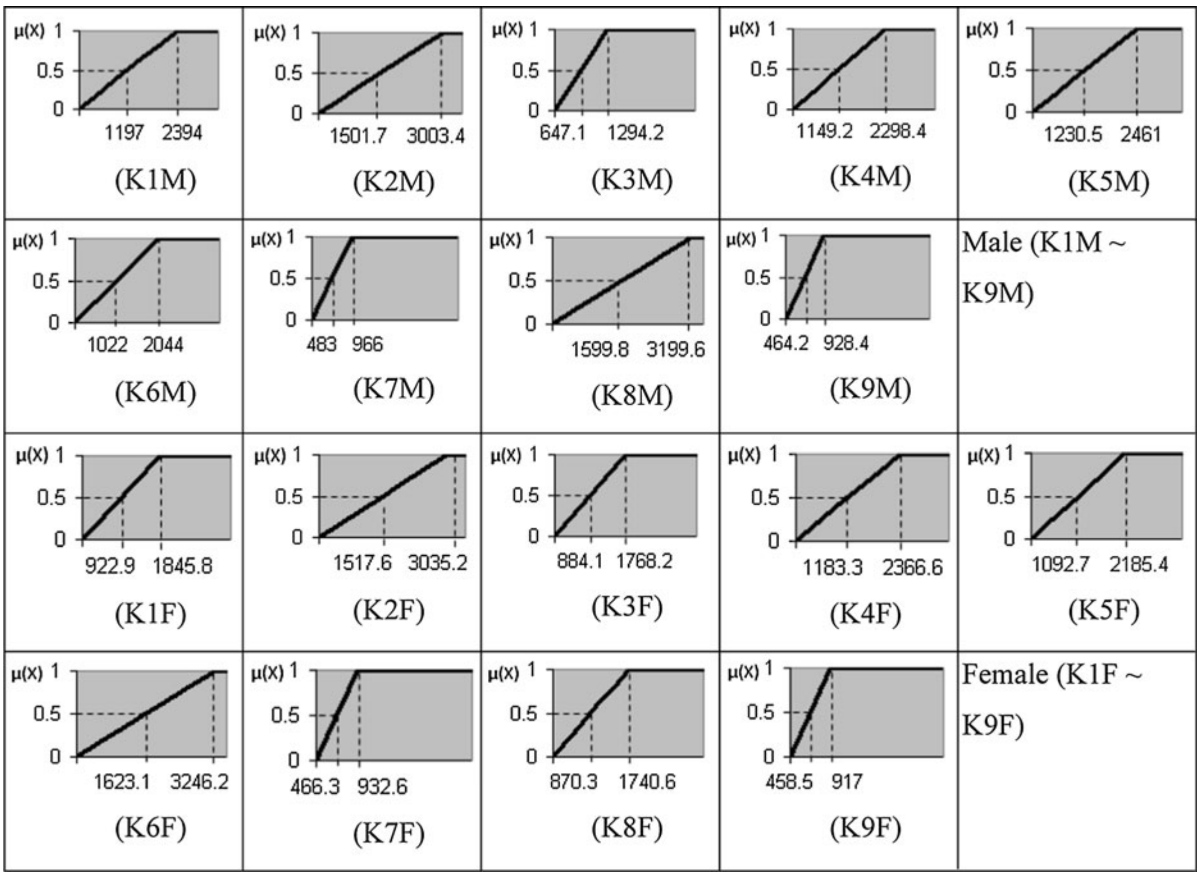
Conclusions and discussion

The three level approaches improve the interpretations of job accessibility by showing the advantages and the limitations for using each approach. Since our goal is to compare among groups and locations together, the universal index enhances comparative analysis in such ways. Based on the universal index, the conditions of job accessibility are not homogeneous between occupations and gender groups as well as among 379 tracts. There are several tracts creating regional job centers attracting more corresponding workers toward them. The numbers of jobs and the patterns of spatial distribution vary by gender and occupation. Unlike the urban classic monocentric model, the CBD is not holding highest job accessibility. Instead, several outer suburban centers share the benefits of higher access to jobs. The comparisons using the universal index are as follow. First, comparison between the occupations shows that the labor situation in Columbus MSA is developed toward urban jobs such as professional and production occupation rather than basic sector economic jobs. Second, gender variations show that men have a significant advantage in job access to K8 jobs over women as women to K6 jobs over men. The gendered nature of the jobs was already well documented in the labor market research. For example, more than 85 % of workers in the transportation and production occupations ($K = 8$). 70 % of workers in computer and engineering related occupations are male workers while 88 % of workers in healthcare support occupations ($K = 6$) are female workers (U.S. Census Bureau 2003). Third, locational variations inform us that locations add gendered dimension to job accessibility even when the job markets does not show gender preferences.

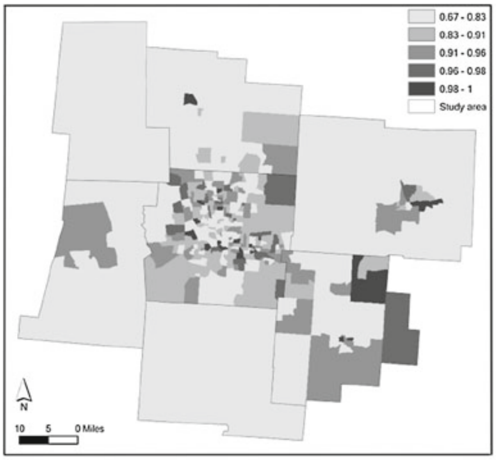
By examining accessibility across multiple axis of dissimilarity including occupation and gender, we are able to detect disparities in accessibility of worker group at the tract level. In spite of availability of spatial data that facilitate such exploration, this has rarely been undertaken in other research. There are 'access-rich' and 'access-poor' groups as well as 'strong access' and 'weak access' locations. This empirical exploration provided the perceptive understanding of the situation of each group at certain location. In addition, this paper demonstrates the usefulness of the multi-level approach of the fuzzy set in evaluating disaggregated job accessibility. The fuzzy set reveals the uncertainty of spatial boundary of a job center that has been ignored in previous studies. In addition, the multi-level approach compares how three indices provide different spatial boundaries of the job center, and helps find more useful indices for certain purposes.

Accessibility is not just a device to explore patterns. Cumulative case study like this paper will improve the usage of job accessibility as an established notion such as a social value of mobility right (Soysal 1994; Urry 2000), and may develop principles of universally accepted level of accessibility. Either as a concept of universal or relative, the interpretation of difference between groups gives insightful meanings to the indices. Although zone-based data are subject to the modifiable areal unit problem (MAUP), this issue can be mitigated by using smaller zones such as block groups or blocks if available. High levels of job accessibility for certain groups may be shaped based on other endogenous reasons such as higher education, no children, flexibility of commuting time, etc. Future research will be pursued to incorporate such geographical and individual details.

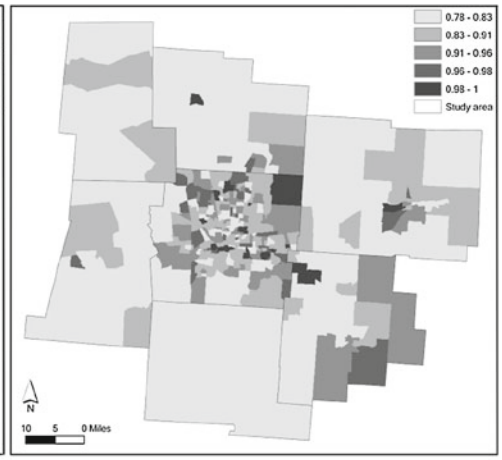
Appendix 1: Crossover profiles for 18 groups illustrated with their fuzzy set MFs



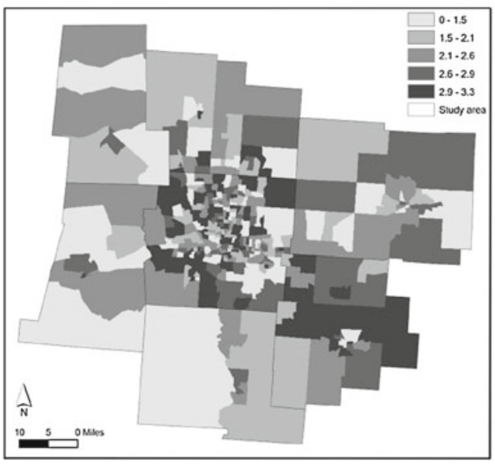
Appendix 2: Uncertainty among the fuzzy sets by gender based on universal index



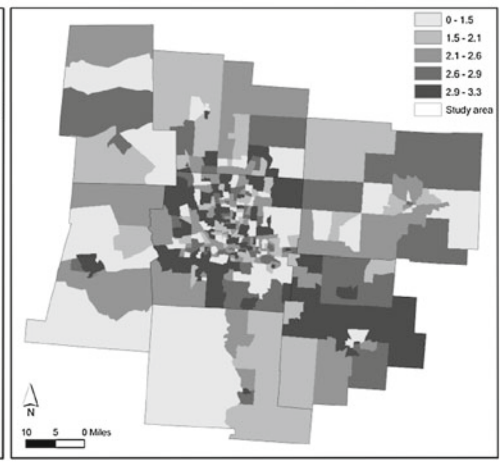
(a) Confusion index (Male)



(b) Confusion index (Female)



(c) Entropy index (Male)



(d) Entropy index (Female)

(e) Variance index (Male)

(f) Variance index (Female)

Appendix 3: Disaggregate doubly constrained spatial interaction model

$$T_{ij}^{kg} = A_i^{kg} O_i^{kg} B_j^{kg} D_j^{kg} \exp(-\beta^{kg} c_{ij}) \tag{12}$$

$$A_i^{kg} = \frac{1}{\sum_j B_j^{kg} D_j^{kg} \exp(-\beta^{kg} c_{ij})} \tag{13}$$

$$B_j^{kg} = \frac{1}{\sum_i A_i^{kg} O_i^{kg} \exp(-\beta^{kg} c_{ij})} \tag{14}$$

$$\sum_j T_{ij}^{kg} = O_i^{kg} \quad \forall i \tag{15}$$

$$\sum_i T_{ij}^{kg} = D_j^{kg} \quad \forall j \tag{16}$$

where kg occupation (k) and gender (g) combination which ensures ($\sum_{kg} T_{ij}^{kg} = T_{ij}$) for all i and j.

$$ACC_j^{kg} = (B_j^{kg})^{-1} = \left[\sum_i A_i^{kg} O_i^{kg} \exp(-\beta^{kg} c_{ij})\right] \tag{17}$$

Spatial interactions by worker' occupation and gender can be modeled by the Eq. (12). Equations (13) and (14) ensure (15) and (16), respectively. Notice that the O_i^{kg} (15) and D_j^{kg} (16) ensure the row sum and column sum in the SI model job accessibility (ACC_j^{kg}). The Eq. (17) representing job accessibility at destinations is disaggregated by worker' occupation and gender using a doubly constrained spatial interaction model. Values for O_i^{kg} and D_j^{kg} for each gender (g) and occupational category (k) are obtained from the CTPP Part 1 (P1) and Part 2 (P2).

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