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Characterizing urban landscapes using fuzzy sets

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A B S T R A C T

Characterizing urban landscapes is important given the present and future projections of global population that favor urban growth. The definition of "urban" on a thematic map has proven to be problematic since urban areas are heterogeneous in terms of land use and land cover. Further, certain urban classes are inherently imprecise due to the difficulty in integrating various social and environmental inputs into a precise definition. Social components often include demographic patterns, transportation, building type and density while ecological components include soils, elevation, hydrology, climate, vegetation and tree cover. In this paper, we adopt a coupled human and natural system (CHANS) integrated scientific framework for characterizing urban landscapes. We implement the framework by adopting a fuzzy sets concept of "urban characterization" since fuzzy sets relate to classes of object with imprecise boundaries in which membership is a matter of degree. For dynamic mapping applications, user-defined classification schemes involving rules combining different social and ecological inputs can lead to a degree of quantification in class labeling varying from "highly urban" to "least urban". A socioeconomic perspective of urban may include threshold values for population and road network density while a more ecological perspective of urban may utilize the ratio of natural versus built area and percent forest cover. Threshold values are defined to derive the fuzzy rules of membership, in each case, and various combinations of rules offer a greater flexibility to characterize the many facets of the urban landscape. We illustrate the flexibility and utility of this fuzzy inference approach called the *Fuzzy Urban Index* for the Boston Metro region with five inputs and eighteen rules. The resulting classification map shows levels of fuzzy membership ranging from highly urban to least urban or rural in the Boston study region. We validate our approach using two experts assessing accuracy of the resulting fuzzy urban map. We discuss how our approach can be applied in other urban contexts with newly emerging descriptors of urban sustainability, urban ecology and urban metabolism.

1. Introduction

Urbanization is a dominant demographic trend and an important component of global land transformation. More than half of the planet's population now lives in cities, up 30% from 50 years ago, and urban areas are gaining 67 million people per year. By 2030, approximately 5 billion people are expected to live in urban areas or 60% of the projected global population of 8.3 billion. Over the next 25 years, rural populations are expected to decline, meaning that all population growth will occur in urban areas (UN, 2009). The developed nations have more urbanized populations. In the US, urbanization is growing at an unprecedented rate as many farmlands, wetlands, forests and other natural ecosystems are being transformed into urban landscapes. Yet these radical transformations of urban form and morphology have not led to changes in how we map or characterize urban landscapes. We continue to be grounded in making maps of human land use that reflect large-scale industrial city-regions and suburbanizing zones. In addition, we make maps intermittently while urban changes are happening rapidly. Wu (2014) in his review of urban ecology notes "cities are spatially heterogeneous, complex adaptive systems". Hence, there is a growing need to implement a methodology for dynamic user-defined urban maps that view cities as spatially heterogeneous systems, the focus of this paper.

A variety of disciplines including urban ecology, urban economics, urban geography, urban planning and architecture, urban politics, and urban sociology bring their own unique perspectives to the study of urban systems. Economic, societal, environmental factors are the main variables conventionally used to characterize *structure*, *form*, and *function* of the urban systems. In addition, governance (policy) and flows of people and goods within urban systems provide additional variables to characterize *system dynamics*, *flows*, *and processes* in the urban system. Fig. 1a shows the five major variables used in urban systems studies as well as six boxes representing fields of study pertinent to this paper. Of the six fields, *urban geography*, *urban sociology*, and *urban design and planning* are mature fields of study while *urban ecology*, and *urban metabolism and urban sustainability* are newer fields. The mature

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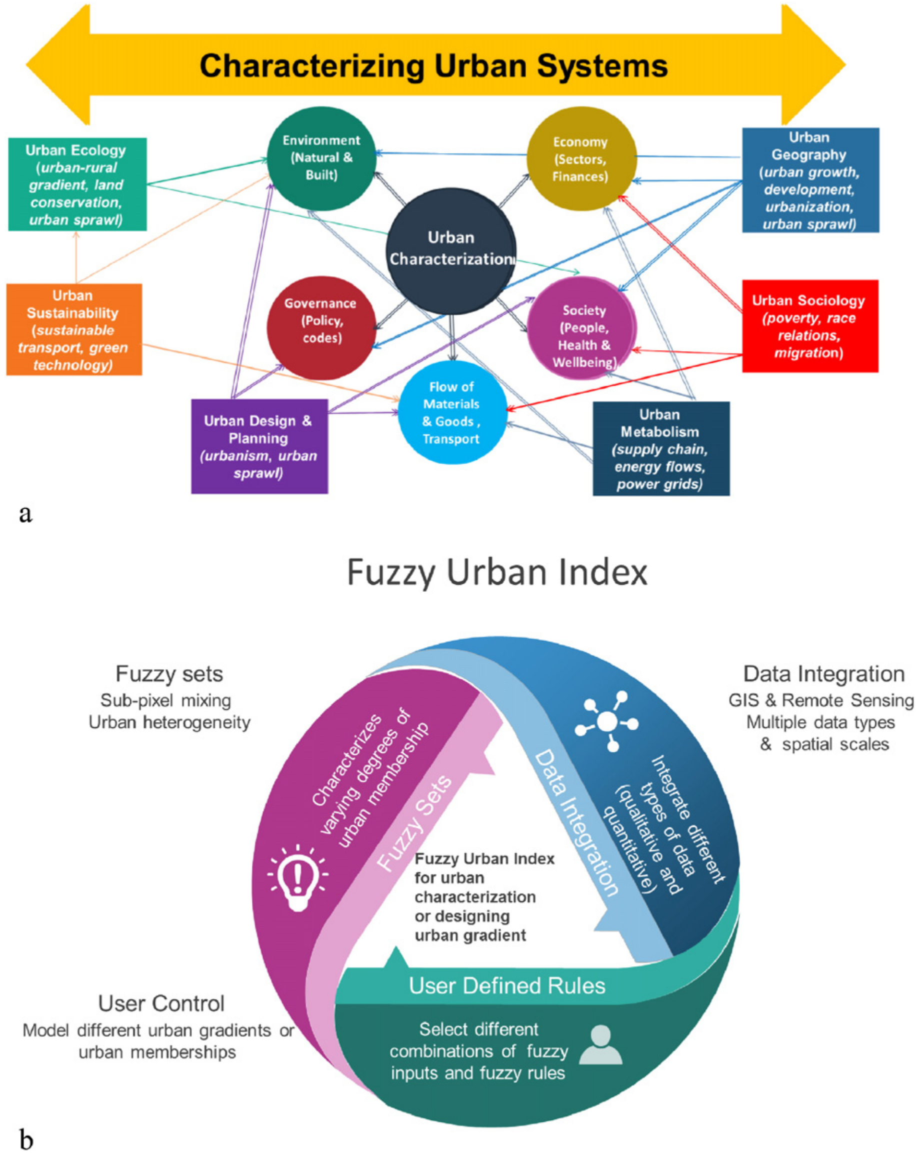

Fig. 1. a: Approaches in characterizing urban systems. b: Our proposed fuzzy inference framework.

fields of urban studies are grounded in social sciences (Champion & Hugo, 2005; Florida et al., 2008; Hall et al., 2006; Lefebvre, 2003; Roy, 2009; Sassen, 2000; Scott, 2001; Soja & Kanai, 2007). The focus in these socio-spatial studies is to identify the many social, demographic, political, environmental and other drivers that are currently reshaping the urban world. These disciplines characterize the urbanization, urban growth, urban sprawl, and urban development, using demographic variables such as employment sectors, population distribution and density.

In the last few decades, newer fields integrating natural and social sciences have emerged to investigate urban systems and address complex problems. Urban ecology, an offshoot of ecology, is an interdisciplinary field that aims to understand the whole city as an ecosystem comprised of both humans and other living organisms that coexist in human-dominated systems (Wu, 2014). Urban ecology has matured from the study of the ecology *in* cities to the ecology *of* cities (Pickett et al., 2008), underscoring the malleability of urban definitions and meanings. Urban sustainability and urban metabolism have emerged as other frameworks. *Urban metabolism* is "the sum total of the technical and socio-economic processes that occur in cities, resulting in growth, production of energy, and elimination of waste" (Kennedy et al., 2007). This area has seen resurgence in interest in the last decade since it provides measures that are indicative of a city's sustainability. One can track energy and material flows at the building or block scale. Urban metabolism is closely linked to sustainability (Gandy, 2004). *Urban sustainability* is concerned with the degree to which physical and socioeconomic systems in cities can be developed and maintained in perpetuity. Resilience in urban sustainability studies is often used as a tool or framework to evaluate the capacity of urban systems to adapt to change (Pickett et al., 2004). In these domains, the issue is the difficulty in characterizing complexity of urban system appropriate to the study objectives and study area (Beatley, 2012). Hence characterizing urban system, integrating inputs from natural and human systems, are significant themes in sustainability and metabolism fields.

Each disciplinary box has arrows linking it to the factors that can be used to qualify and quantify specific urban concepts. For example, in urban geography, (see top right box in Fig. 1a), *urban growth* refers to the increase in urban area while *urban development* broadly refers to the social, cultural, economic and physical development of cities, as well as the underlying causes of these processes. *Urbanization* is the result of human migration from rural to areas (towns and cities). *Urbanization* (McCarthy & Knox, 2005) involves a complex set of economic, demographic, social, cultural, technological, and environmental processes that result in an increase in the proportion of the population that lives in towns and cities. Thus, this box is linked to economy, society, environment, and governance. *Urbanism* (Talen, 2005) (in urban design box) often refers to social character of urban life and is also used to refer to the interaction of inhabitants of urban areas with their built environment. Urbanism can also refer to the degree of urbanization. *Urban planning* (see lower left box in Fig. 1a), refers to the design and management of the urban environment including the both the natural elements (such as air, water, and soil) as well as human built landscape (Hall & Tewdwr-Jones, 2010). In addition, some terms are used in multiple disciplines. For example, *urban sprawl* refers to the unplanned and uncontrolled spreading of urban development into rural areas adjoining the edge of a city (Dodson & Gleeson, 2009; Hutchison, 2009). This concept is utilized in urban geography, as well as urban design and planning and urban ecology. Terms such as *urban sustainability*, *metabolism*, *urbanization*, *urbanism*, and *urban sprawl* are fuzzy concepts since they cannot be precisely defined and vary across studies. Fuzzy sets provide a method to quantify these concepts and include them in urban studies.

Urban characterization is central in the urban context. At the simplest level, the main variables conventionally used to distinguish rural from urban areas are variables such as population size, population density in built-up areas, predominant economic activities, and administrative boundaries in urban geography. In addition, there are user defined classes such as commercial, residential, and suburban. Often, such user defined rules are made in a subjective classification process and not quantitatively articulated or generalized. Given the nature of mapping in the age of geospatial technologies, there is a greater need for better articulation and transparency in rule formulation to characterize urban areas. Another approach to urban characterization is to treat the urban class as a continuous variable to describe urban–rural transition. The gradient framework has been used to test hypotheses on the impacts of urban development on ecological or other processes (Alberti, 2008; Cadenasso et al., 2007). In landscape ecology, urban gradient is derived using landscape composition and spatial heterogeneity (Alberti et al., 2001). Some recent studies such as urban heat island effect (Yuan & Bauer, 2007), sea level changes (Nicholls & Cazenave, 2010), and distribution of urban–suburban temperatures (Stewart & Oke, 2012) analyze differentials along a gradient across urban areas based on land use, specifically urban land use. A more realistic urban gradient could be formulated based on a coupled human–natural system integrating both sets of variables. Our proposed approach integrates inputs in the coupled human–natural system based on fuzzy sets and fuzzy inference system (Fig. 1b).

Prior research has described the use of fuzzy sets to derive new measures of urbanization. Abed and Kaysi (2003) define a composite fuzzy index of intensity of urbanization based on integration of three variables related to urban density, land use and activity in Beirut. Heikkila et al. (2002) adopted Kosko's hypercube and developed three metrics to measure extent of urbanization, level of fuzziness, and degree of entropy, to characterize levels of urban membership typical in cities of China, and other Asian countries. Specifically they focus on the issue of characterizing peri-urbanizing (desakota) systems. Fuzzy sets has also be used to model dynamics in urban systems (Dragićević, 2004) as well as in classification of urban land cover at a variety of spatial scales (Chanussot et al., 2006; Islam & Metternicht, 2005; Shackelford & Davis, 2003; Zhang & Foody, 2001). Fuzzy sets have also been used to integrate GIS and remote sensing data in order to identify detailed land use classes in urban areas (Zhan et al., 2000). Fuzzy urban land use classes are based on fuzzy class memberships using fuzzy criteria or rules. Fuzzy membership values can then enable the derivation of uncertainty levels. Thus fuzzy sets offer several advantages in spatial sciences from characterizing urban spatial heterogeneity, modeling urban membership, integrating spatial, spectral and other ancillary information and deriving uncertainty estimates.

Expert system (ES) approaches, developed over the last two decades, have classified urban land cover combining remote sensing information with ancillary contextual information in the US and other regional contexts to derive 7–10 urban land cover classes (Choi & Usery, 2004; Stefanov et al., 2001; Wentz et al., 2008). The ultimate goal is to build general expert system of rules that can be used with minimum modifications in other regional contexts. Wentz et al. (2008) demonstrate the practical challenges (including map data) involved in transferring expert system developed in one urban context (Phoenix) to another (New Delhi). More recently, a neural-fuzzy approach for land cover classification was developed that used a fuzzy inference system and a data mining technique to derive land use and land cover (LULC) patterns using remote sensing data (Pimentel et al., 2015).

Three broad trends impact measuring, mapping and characterizing urban areas in the 21st century. First, there is an increasing need to integrate both human and natural elements in order to better model and map the coupled human–natural urban system. Second, mapping requires a data-driven approach that easily integrates remote sensing, GIS, and other spatial data for mapping and characterizing urban areas easily at a variety of spatial scales. Third, many applications require participatory user driven mapping, where the user can dynamically define urban classes and produce different urban characterizations by selecting levels and combinations of different inputs unique to fit their study objectives and application domains.

Here we propose a fuzzy inference system that addresses the three broad trends described above, applied as a case study in greater Boston, and incorporating metrics in the emerging domains of urban sustainability, ecology, and metabolism.

2. Fuzzy inference system

Zadeh (1965) introduced the notion of fuzzy sets to describe ambiguous or partial set membership. Unlike in the conventional (or "crisp") set theory, sets, in which all elements are constrained to have full membership, the limit of the fuzzy set is not precisely determined. Instead, there is a gradual transition from non-membership of elements in a set, through their partial membership, to membership (Dubois & Prade, 1980). This gradual transition is described by the so-called membership function m_A, where A is a set of fuzzy numbers. When urban characterization is treated as a fuzzy concept, the constituent parcels or pixels may exhibit varying degrees of membership from one of being *highly urban* to *somewhat urban* to *least urban*. Fuzzy logic is therefore able to model the world in imprecise terms, similar to how our brains process imprecise or uncertain or vague information, and respond with precise action.

We propose a fuzzy sets concept of urban characterization using fuzzy inputs. We use the term *urban characterization* to denote the multi-faceted nature, extent and magnitude of urban areas in thematic maps. Threshold values are defined to derive the rules of membership for each input, and various combinations of rules offer a greater flexibility to characterize the many facets of the urban areas. Fuzzy sets can harmonize land use and land cover data into one database. In addition, they enable the user to define specific characterizations of urban class using different combinations of the input variables in the database appropriate for the application at hand. The application of the fuzzy set theory to rule-based expert system offers advantages in terms of: (1) representation and processing of uncertain data in the form of fuzzy sets (e.g. a highly vegetated region), and (2) representation of linguistic rules that integrate two or three inputs to define a fuzzy urban characterization class.

A fuzzy inference system (FIS) uses fuzzy set theory to map inputs (features in the case of fuzzy classification) to outputs (classes in the case of fuzzy classification). Knowledge is represented by if–then fuzzy rules that consist of two parts: an antecedent part stating conditions on the input variable(s) and a consequent part describing the corresponding values of the output variable(s) (Ross, 1995). For example: IF the level of vegetation density is low, THEN urban index should be high, where the terms 'level' and 'urban index' are fuzzy variables represented by fuzzy sets ('high' and 'low').

The starting point of constructing a fuzzy system is to obtain a collection of fuzzy if–then rules from experts or from prior research. Fuzzy rules are always written in the following form: *if* ($input_1$ *is membership* $function_1$) *and/or* ($input_2$ *is membership* $function_2$) *and/or … then* ($output_n$ *is output membership* $function_n$). In the urban context, if vegetation index is high ($input_1$) and population density ($input_2$) is low then output value of urban membership is low. This process of taking an input such as population density and processing it through a membership function to determine what we mean by "low" urban membership is called fuzzification. The Boolean operators "and"/"or" in the fuzzy rule have to be defined.

The fuzzified inputs have to be combined according to the fuzzy rules to establish rule strength. The fuzzified inputs become the antecedents of the fuzzy rules; the fuzzy operator (AND or OR or NOT) is used to obtain a single number that represents the result of the antecedent evaluation. Fuzzy combinations are also referred to as "T-norms".

Fuzzy "or"

$$A \cup B = T(\mu_A(X), \mu(X))$$

where μ_A is read as "the membership in class A" and μ_B is read as "the membership in class B″. There are many ways to compute "or". The two most common are:

1. Zadeh Technique — $\max(\mu_A(x), \mu_B(x))$: This technique, named after the inventor of fuzzy set theory simply computes the "or" by taking the maximum of the two (or more) membership values. This is the most common definition of the fuzzy "or".
2. Product — $(\mu_A(x) * \mu_B(x))$: This technique computes the product by multiplying the two membership values.

Both techniques have the following two properties:

$$T(a, 0) = T(0, a) = a$$

$$T(a, 1) = T(1, a) = 1.$$

Fuzzy "and"

$$A \cap B = T(\mu_A(X), \mu_B(X))$$

1. Zadeh Technique — $\min(\mu_A(x), \mu_B(x))$: This technique, named after the inventor of fuzzy set theory simply computes the "and" by taking the minimum of the two (or more) membership values. This is the most common definition of the fuzzy "or".
2. Sum minus Product — $(\mu_A(x) + \mu_B(x) - u_A(x) * u_B(x))$: This technique uses the difference between the sum of the two (or more) membership values and the product of the membership values.

Both techniques have the following two properties:

$$T(0, 0) = T(a, 0) = T(0, a) = 0$$

$$T(a, 1) = T(1, a) = a.$$

We use the Sugeno inference system to compute a singleton output. A fuzzy singleton can be defined as a membership function that is a single spike at a particular point while zero elsewhere (Takagi & Sugeno, 1985). The resulting output membership function is a fuzzy set that needs to be defuzzified for mapping the output classes (similar to the input classes). We describe the data and implementation of the fuzzy inference system for our study in the next section.

3. Data and methodology

In this paper, we introduce a new database driven approach to characterize urban characterization using fuzzy sets theory. We create a fuzzy inference system (FIS) that is capable of combining different input dataset using pre-defined rules to characterize difference levels of urban characterization in urbanized areas. In this section, we will explain the basis of fuzzy sets concept as well as the fuzzy inference system relevant to this study.

3.1. Study area

The study area is the Boston Metropolitan area, defined as the city of Boston and surrounding suburban neighborhoods, stretching 40 miles to the east to west and 30 miles north to south. The study area includes six counties — Suffolk, Essex, Middlesex, Norfolk, Plymouth and Worcester counties and encompasses 103 towns including Boston, Revere, Plymouth, Brookline, Cambridge and Newton.

3.2. Input data

We illustrate the flexibility and utility of the Fuzzy Urban Index approach using five inputs selected to best and easily characterize the CHANS framework: (1) land use, (2) population, (3) Normalized Difference Vegetation Index (NDVI), (4) Vehicle Miles Traveled (VMT), and (5) commercial VMT. Population, VMT, and commercial VMT represent the human dimensions while NDVI represents natural systems in the CHANS framework illustrated in Fig. 1a. Land use variable incorporates the feedbacks between both dimensions in the CHANS framework. All of the variables are easily available. Users can incorporate other inputs to characterize the CHANS framework of their study area. For example, variables related to temperature drought, road network, zoning and earthquake risk may be more relevant in the context of urban sustainability study of Los Angeles.

The inputs used in this study have varying spatial resolution with the finest being 30 m and the coarsest being 250 m. The data are integrated into a GIS with a spatial resolution of 250 m after preprocessing for georegistration and projection.

Landuse (*2005*): This layer is a statewide, data layer of land cover/land use, created by the state agency called MassGIS using semi-automated methods, and based on 0.5 m resolution digital ortho-imagery captured in April 2005 (see Fig. 2). Urban studies have widely used this land use data consisting of 33 categories. Breunig (2003) used the land use/land cover data from Massachusetts to characterize the growth of residential development as well as examine urban sprawl. The seminal publication of Mass Audubon "Losing Ground" (DeNormandie, 2009) used this data to discuss trends in changes to the natural environment in the different towns of the state. A more recent study by Raciti et al. (2012) used this data to estimate carbon flux.

Population Density (*2010*): This layer is a statewide, data layer of the population density data calculated based on the 2010 census data from MassGIS. The unit of the population density is the number of people per square kilometer derived from the census data about households. Population density increases from west to east in the state. Population density has proved useful in assessing traffic patterns and energy consumption. This population density measure is more reflective of "night based" and weekend population density, and does not capture the daily variation of population density during week days (Janelle & Goodchild, 1983).

NDVI (*2010*): Prior remote sensing studies have used the normalized differential vegetation index, commonly known as NDVI, in studying land use patterns over time. NDVI is calculated, on a per-pixel basis, as the normalized difference between the surface reflectance values of red and near-infrared bands from a remote sensing image. The biophysical interpretation of NDVI is the fraction of absorbed photosynthetically active radiation (PAR), which is an accurate indicator of greenness of the

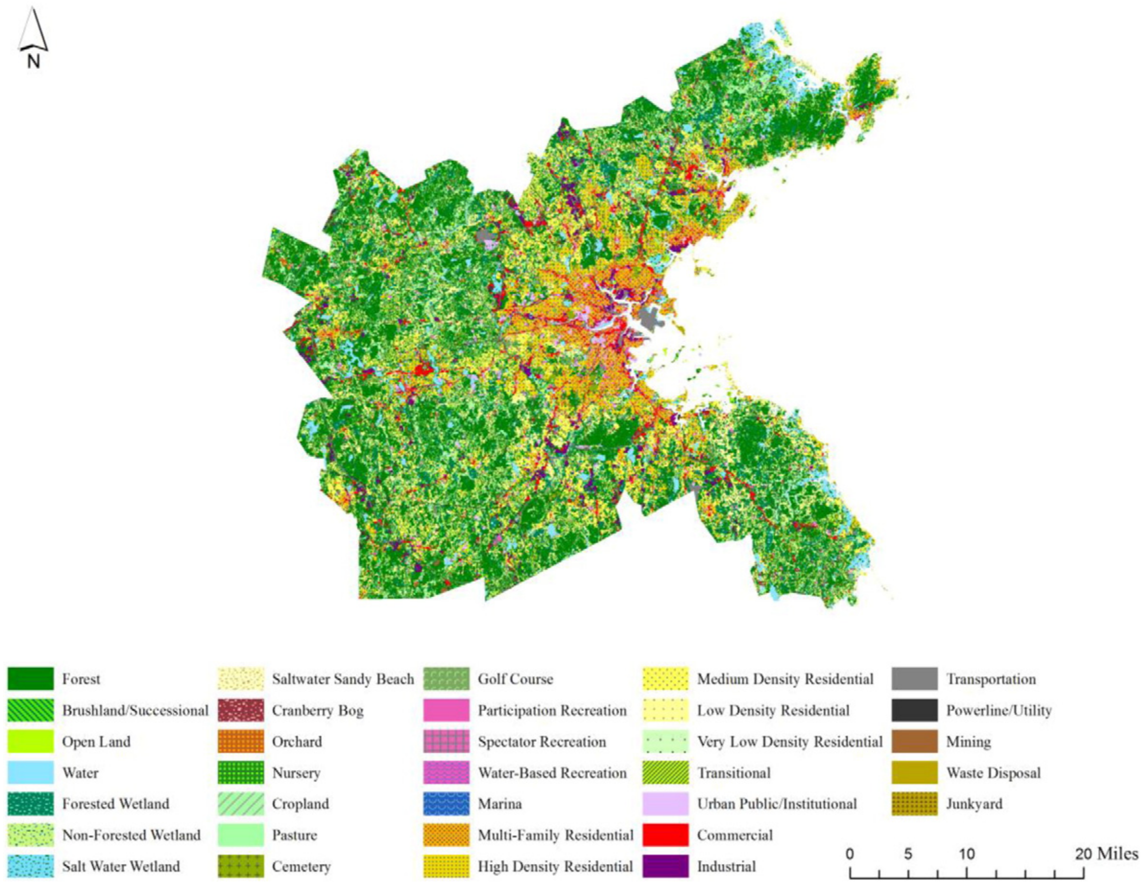

Fig. 2. Land use classes in the Boston study region (Source: MassGIS).

surface and is widely used measure of vegetation. For example, Sexton et al. (2013) studied urban land cover changes using impervious surface from Landsat data for the Washington, D.C.–Baltimore, MD megalopolis from 1984 to 2010. NDVI was estimated to differentiate vegetated from non-vegetated surfaces across urban, suburban, and agricultural land uses.

In the present study, two Landsat-5 March images (30 m resolution) over Boston study area were downloaded (from USGS) and atmospherically corrected using LEDAPS (Masek et al., 2006) (see Fig. 3). The two images are merged, converted, clipped and resampled to the 250 m resolution adopted for the study. NDVI is then calculated using the surface reflectance in red and near-infrared bands of the pre-processed Landsat image.

VMT (*2010*): The Vehicles Miles Traveled (VMT) data is a unique dataset of the odometer readings from annual safety inspections for all private passenger vehicles registered in Metro Boston. The spatial layer is a statewide 250 m by 250 m grid cell layer developed by MassGIS (Diao, 2010; Diao & Ferreira, 2010). The data and units used in this study are daily miles traveled by passenger vehicles per household that ranges between 0 to over 200 miles. (Any cell with more than 200 miles traveled per household is reassigned a value of 200 for the purpose of our analysis.) Diao and Ferreira (2010) showed the utility of VMT by examining its relationship to various built-environment and demographic characteristics. This is a unique dataset that could be utilized in the study to capture travel patterns of commuters and the city traffic.

CVMT (*2010*): Commercial Vehicle Miles Traveled (CVMT) can also be used to characterize urban characterization since higher density of CVMT could denote higher urban travel density. (Any cell with more than 500 miles traveled is reassigned a value of 500 for the purpose of our analysis.) Studies on the interrelationship between land use and commercial travel are useful in characterizing the economic activity of the region (Badoe & Miller, 2000). Other easily available data such as location of business from sources such as Dunn and Bradstreet and employment statistics from census can also provide commercial activity in the city and may be more relevant than CVMT.

3.3. Fuzzy Urban Index

We now describe how the general CHANS framework is implemented using fuzzy sets. The general methodology to set up a fuzzy inference system for this study is modified from Knapp (1998). It consists of the following steps: (1) convert the input distributions into fuzzy membership functions, (2) define a set of fuzzy rules, (3) apply rules and estimate rule strength for each set of inputs, (4) aggregate the rule outputs to derive a measure of fuzzy urban characterization, and (5) create thematic fuzzy map labels. Section 2 describes fuzzy inference process in relation to our research. Our output index is called Fuzzy Urban Index (see Fig. 4).

3.3.1. Convert the input distributions into fuzzy membership functions

The objective of creating fuzzy membership functions is to take the crisp inputs, x_1 and y_1 (for example *vegetation index* and *population density*), and determine the degree to which these inputs belong to each of the appropriate fuzzy sets ranging from 0 to 1. The membership functions could then represent *low* vegetation index or *high* population density. For the purpose of this study, the five inputs were fuzzified such that each input has five different linguistic sets — *very high*, *high*, *medium*, *low*, and *very low* memberships of each of the five inputs shown in Table 1.

We adopted two approaches in defining the membership functions: prior empirical approaches in defining urban classes, and examining the

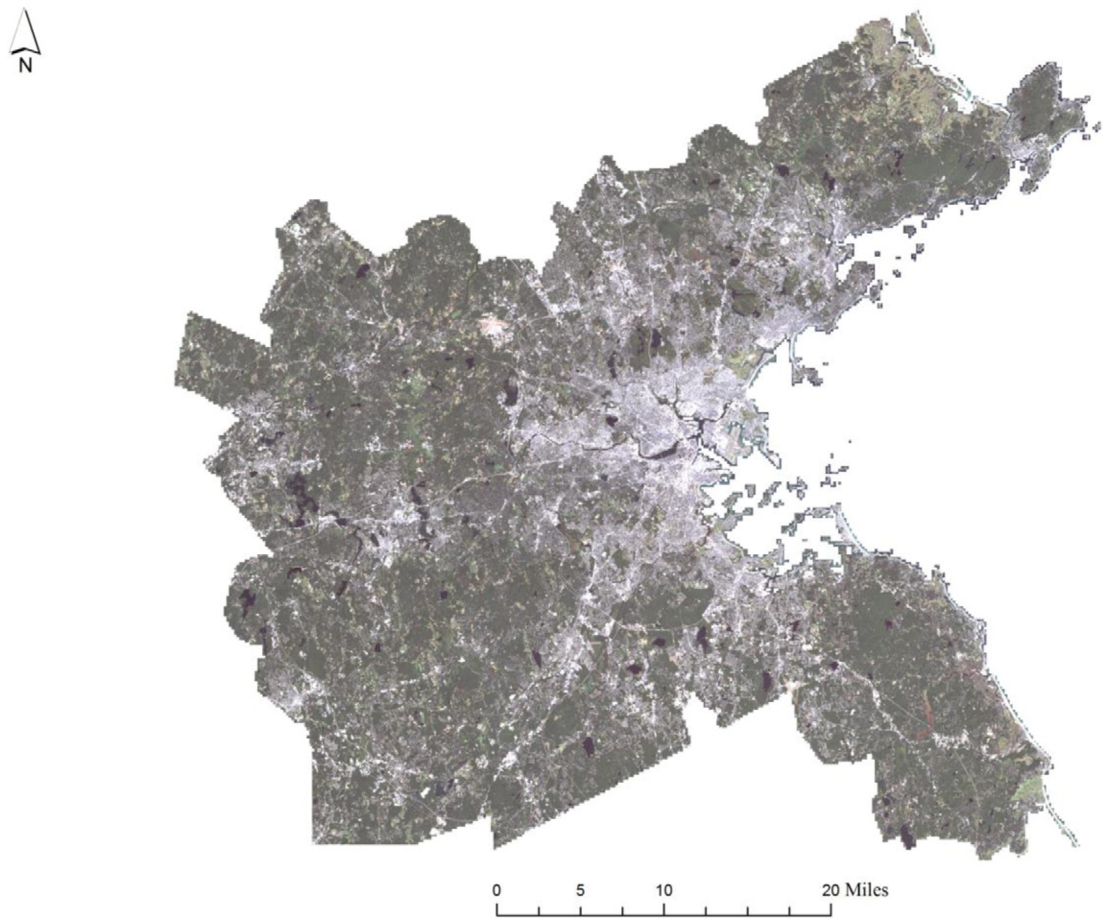

Fig. 3. Landsat true color image of the Boston study region.

distributional characteristics of different input values to adjust the fuzzy membership intervals.

Land use: There are 21 (MassGIS, 2005) urban land use categories in the statewide McConnell land use System including the following classes: Multi-Family Residential, High Density Residential, Medium Density Residential, Low Density Residential, Commercial, Industrial, Urban Institutional and Transportation (see Fig. 2). Appendix A displays the complete categories and its associated empirically derived index (between 0 and 100) to characterize the urban characterization value (see Appendix). A class value of 100 characterizes artificial impervious built area while a class value of 0 represents all natural vegetation in that polygon (Arnold & Gibbons, 1996).

Population: The US Census defines a population density value of 1600 per square km to characterize *high density*. We have adopted this value to describe a fuzzy membership for high population density and added other categories around it using class distributional statistics centered on the mean and deviation around the mean.

NDVI: Prior research (Myneni et al., 1995; Weier & Herring, 2000) describes high and low NDVI values in terms of land cover noting that *very high* NDVI represents high amount of greenness on the surface, while low NDVI represents built areas or water. We have used a membership value of [−1, 0.2] to denote *very low* NDVI, [0.2, 0.4] for *low*, [0.4, 0.6] for *medium*, [0.6, 0.8] for *high* and [0.8, 1] for *very high* (Table 1).

VMT and CVMT: On the other hand, we used equal intervals to describe VMT membership function. The quality of each resulting map (Fig. 5) made with the input membership function was carefully evaluated by two experts and values adjusted to represent Boston's urban characterization most appropriately. This step was necessary given we wanted to validate the resulting map.

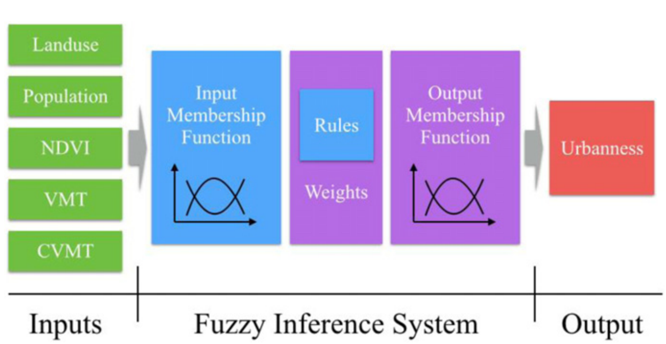

Fig. 4. Fuzzy inference methodology used in the present study.

3.3.2. Define a set of fuzzy rules

While prior urban studies do not explicitly contain rules of urban characterization, (Besussi et al., 2010; Masek et al., 2000; Pickett et al., 2011; Whitehand & Carr, 2001), we used these studies to formulate

Table 1
Defining five levels of fuzzy input membership.

Input	Very low	Low	Medium	High	Very high
Land use	0–20	20–40	40–60	60–80	80–100
Population	0–50	50–500	500–1600	1600–10,000	10,000–30,000
NDVI	0–0.2	0.2–0.4	0.4–0.65	0.65–0.8	0.8–1
VMT	0–20	20–40	40–60	60–80	80–200
CVMT	0–20	20–50	50–100	100–300	300–500

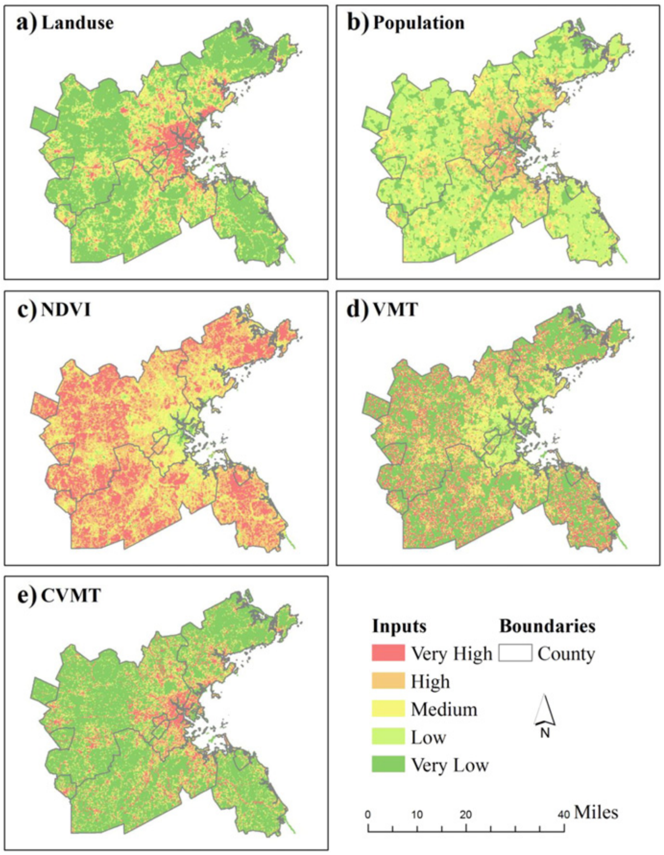

Fig. 5. Urban characterization based on Fuzzy Urban Index.

our rules of urban characterization. Table 2 shows a set of 18 simple rules using "AND" fuzzy operator and each rule results in a specific output *urban characterization* class. We give examples of some prior studies that have examined or used similar rules. For example, Rule 1 states that if NDVI is *very high* and land use is *very low*, then urban characterization is *very low* (Bauer et al., 2004; Carlson & Arthur, 2000), while Rule 7 states that if CVMT is *very high* and land use is *very high*, then urban characterization is *very high* (for example Frank et al., 2000). Some rules in Table 2 show the impact of input combinations on the fuzzy index. Rule 2 shows that a combination of high population density and low VMT can lead to very high degree of urban membership, characteristic of urban city centers. On the other hand, Rule 13 states that *low* population and *high* VMT results in low degree of urban characterization, true of suburbs; while Rule 14 states that *low* memberships of inputs for land use, population, and VMT and a *high* membership in vegetation index can result in *low* urban characterization.

3.3.3. Apply rules and estimate rule strength for each set of inputs

Table 2 captures the consequences of combining inputs to find the consequent urban characterization class. For example, *very high* population and *very low* NDVI results in a *very high* urban characterization class. The linguistic characteristics are then converted into a fuzzy set between 0 to 1 using an equal interval membership function with 1 representing the highest degree of urban characterization and 0 representing the lowest.

3.3.4. Aggregate the rule outputs to derive a measure of fuzzy urban characterization

In the list of rules used in this study, there are five rules characterizing high urban characterization, four rules for very low urban characterization, and three for low, medium, and very high urban characterization classes respectively. The rules listed in Table 2 must be combined in some manner in order to make a map decision. Thus, each pixel on the map has to be assessed using each of the 18 rules. Typically only 1–3 rules would apply in the context of 1 pixel given the distribution of the input membership levels. The fuzzy rules incorporate the inherent mixtures that characterize the urban class in each pixel. More rules can be built that captures the unique spatial context of an urban landscape. The final result is the output class for characterizing the urban characterization. The final map was made using a 3 × 3 filter to capture the local context and reduce the salt and pepper appearance of the pixels. The local spatial context can help in differentiating these types of outliers, for example a remote building in a rural context and a park in a dense urban neighborhood. In this study, every rule has a weight (a number between 0 and 1). Our two experts had higher confidence ratings for very low and very high membership values while they had the least confidence around medium. Hence, rules utilizing very low and very high membership values have a weight of 1 while low and high membership values have a weight of 0.9, and medium membership values have a weight of 0.8. The selection of weights was tested with various valuations, and the best one was selected based on expert assessment of the resultant maps of Boston in the final step. However, future research should focus on how different weights could simulate different realizations of maps across different user communities and the relationship to the objectives of the study (for example, conservation or urban planning).

Table 2
Defining rules for fuzzy index of urban characterization.

ID	Prior research	Rules	Land use	Population	NDVI	VMT	CVMT	Urban
1	Imhoff et al. (2000)	And		VHigh	VLow			VHigh
2	Diao and Ferreira (2010)	And		VHigh		Low		VHigh
3	Bronzini et al. (2008)	And	VHigh				VHigh	VHigh
4	Li and Weng (2005)	And		High	Low			High
5	Herold et al. (2005)	And	High	High				High
6	Xia (2011)	And	High			Low		High
7	Herold et al. (2005)	And	VHigh	VLow				High
8	Herold et al. (2005)	And	VHigh	Low				High
9	Yuan and Bauer (2007)	And	Medium		Medium	Medium		Medium
10	Diao (2010)	And		Medium		Medium		Medium
11	Pataki et al. (2009)	And			High			Medium
12	Yuan and Bauer (2007)	And	Low		High			Low
13	Ewing and Cervero (2001)	And		Low		High		Low
14	Clifton et al. (2008)	And	Low	Low	High	Low		Low
15	Masek et al. (2000)	And	VLow		VHigh			VLow
16	Diao (2010)	And	Not High	VLow		VLow	Not VHigh	VLow
17	Hansen et al. (2004)	And	VLow	VLow	VHigh			VLow
18	Herold et al. (2005)	And	VLow	Low				VLow

3.3.5. Create thematic fuzzy map labels based on Fuzzy Urban Index

The resulting output fuzzy set can be defuzzified into distinguishable classes for obtaining a crisp output/class. In our study, the output fuzzy set is divided into five classes using equal interval classification (see Fig. 7). These classes correspond to the five levels of urban characterization (*very high*, *high*, *medium*, *low*, and *very low*).

4. Results

4.1. Fuzzy Urban Index

Our index called the Fuzzy Urban Index can differentiate spatial heterogeneity or characterize the multi-faced nature of urban areas in the Boston region. Panels in Fig. 6 show the five levels of fuzzy membership of each input enabling visualization of subtle differentiation. The traditional land use map (Fig. 2) displays various classes such as *urban*, *industrial*, *low* and *high density residential* regions. In contrast to this map, Fig. 5a is the fuzzy land use membership map of urban variation across the Boston region. Similarly, Fig. 5b shows the fuzzy population density map that mainly characterizes Boston core region as *very high* urban class while *medium* and *low* urban classes are distributed elsewhere on this map.

In contrast, Fig. 5c shows NDVI map that indicates that Boston is somewhat green and not highly urban since there is some vegetation surrounding the core urban region. The high level of greenness in the suburbs matches the apt label "leafy suburbs". Fig. 5d and e show the VMT and Commercial VMT maps that display a *very high* urban class within 20 km of major transportation routes indicative of economic activity and commuting patterns. Thus, using fuzzy sets, we can describe five levels of urban classes some of which could have been labeled as non-urban in traditional thematic maps.

Fig. 6 shows the number of pixels in each fuzzy input class characterizing the fuzzy urban class. It can be seen that *very low* urban class is the most dominant class using each of the five inputs indicating the heterogeneous distribution of the inputs given the current definition of fuzzy membership functions adopted in this study. Hence, the next step is to combine the fuzzified inputs according to the fuzzy rules (Table 2) to establish the Fuzzy Urban Index.

Fig. 7 shows the corresponding output map of the proposed Fuzzy Urban Index. Note this would involve defining many map overlay operations in traditional GIS analysis.

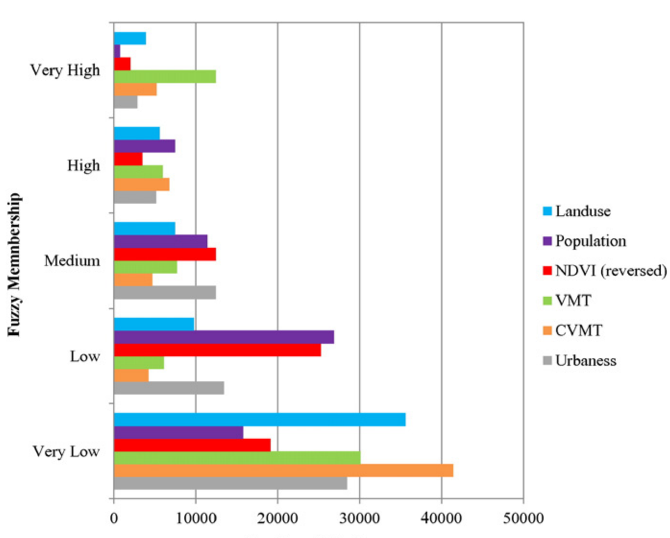

Fig. 6. Distribution of fuzzy input and output membership classes.

4.2. Characterizing fuzzy urbanness of counties

There are six counties in the study area as seen in Table 3. Each county's Fuzzy Urban Index urban classes are contrasted using traditional land use categories (see Fig. 8). In general, there is a correspondence between the class "others" and the *very low* fuzzy urban classes using the Fuzzy Urban Index methodology.

The advantages of the fuzzy approach can be analyzed seeing how traditional classes such as *commercial* and *highly built* fall into the fuzzy urban classes using our proposed methodology. Suffolk county's *commercial* and *highly built* traditional map classes align with *very high*, *high* and *medium* fuzzy urban classes while Plymouth's *low built residential* aligns with *medium* and *low* fuzzy urban class in Fuzzy Urban Index. Thus, the Fuzzy Urban Index methodology helps us in quantitatively characterizing the multi-faceted nature of the traditional urban map label.

4.3. Validation of fuzzy urbanness classes

It is important to check the validity of our approach to understanding the strengths and limitations of Fuzzy Urban Index. Two experts (with 4–5 years of remote sensing and aerial photo interpretation experience) validated the five fuzzy urban classes derived using Fuzzy Urban Index shown in Fig. 7. A sample of 100 pixels, 20 in each of the five fuzzy urban classes, were randomly selected for validation. Experts' knowledge of the study aided in the sampling design. The validity of the sites was checked using a high resolution imagery of the study region. Each expert knew the research objectives and was asked to evaluate the 100 pixels using five linguistic labels of fuzzy urban using methodology described (Gopal & Woodcock, 1994). Table 4 shows the experts' assessments based on fuzzy operators, Zadeh max($\mu_A(x)$, $\mu_B(x)$) and Zadeh min($\mu_A(x)$, $\mu_B(x)$) (Zadeh, 1965). The former measure is liberal and allows any degree of agreement to the ground truth among experts while the latter is strict and defines a match only when both experts agree and choose the highest degree of match to the ground truth.

The results in Table 4 show that the overall accuracy using Zadeh max is around 78.9% while accuracy drops to 46.84% using Zadeh min (Zadeh, 1965). The accuracy results also indicate that experts agree 78.9% of the time in scoring classes using a liberal definition of agreement while they agree only 46.8% when using a very conservative definition of agreement. Highest agreements are recorded for high and very high as well as very low fuzzy urban classes. The results suggest that the medium urban class has the lowest agreement among the two experts reflecting the difficulty in determining these classes and variations among experts in scoring this class.

4.4. Nature of misclassifications using Fuzzy Urban Index

Fig. 9 shows that there may be some limitations in Fuzzy Urban Index that led to the following types of misclassification errors. First, the fuzzy inference rules in Fuzzy Urban Index is overestimating the fuzzy urban in high impervious surfaces such as the parking lot and airports. These are given a score of *high* or *very high* fuzzy urban in the model while the experts are rating these areas as being *medium* urban based on the context and knowledge of airports and parking lots. Fuzzy Urban Index needs to have more explicit rules for recognizing airports and parking lot and score them lower in terms of the of index of fuzzy urban. Second, the simple rules built in Fuzzy Urban Index does not cover all contexts of fuzzy urban such as office buildings in downtown Boston that empty out at nights and are not places of residence. The default rule in Fuzzy Urban Index scores such regions with a medium score. This scoring may result in an error when the expert judges office areas differently as high or very high urban class. Third, the expert may make "errors" since the expert is using a high-resolution imagery of the study region and may not know the exact population of the pixel used in the Fuzzy Urban Index rule base. A pixel may have a

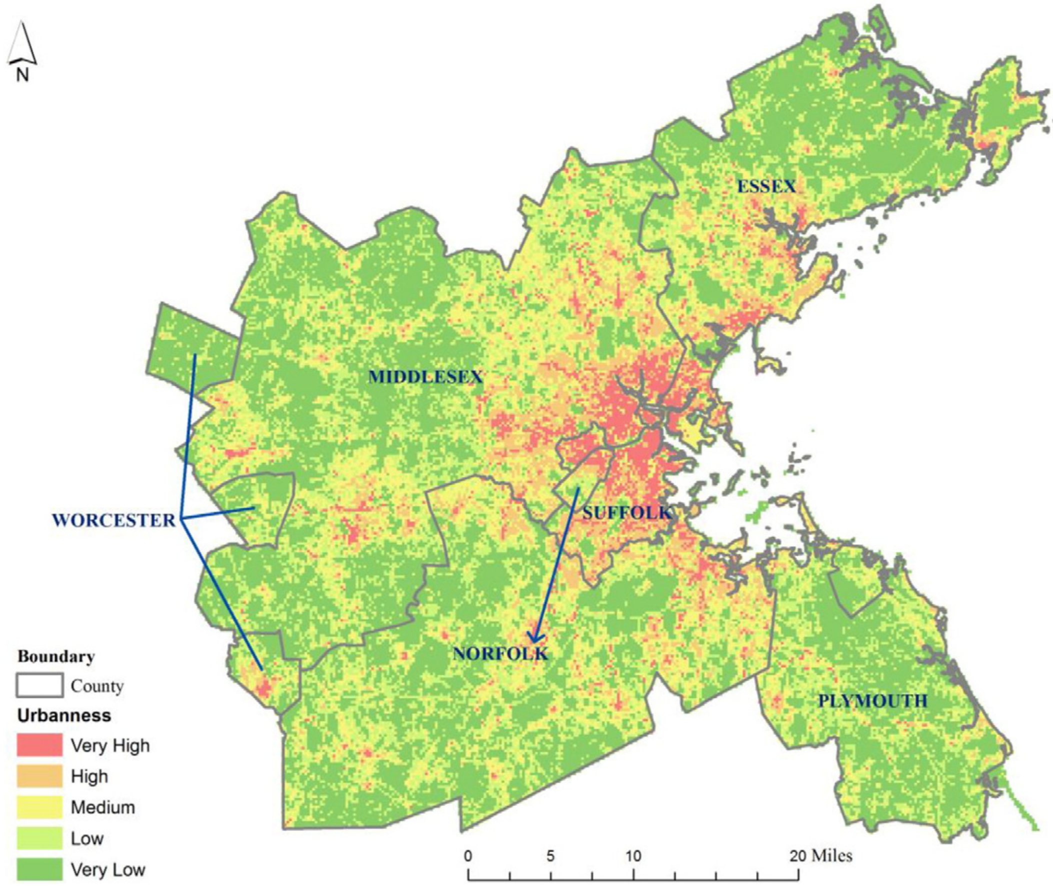

Fig. 7. Fuzzy urbanness map of the Boston study region using Fuzzy Urban Index.

higher-than-expected population which cannot be interpreted by the expert using only satellite imagery during validation. For the purpose of a consistent validation process, the experts' opinion is considered as the ground truth and may sometimes lead to errors. Fourth, a classic error occurs as a result of the "edge effect" where McMansions in the suburbs are located in the middle of woods or a vast expanse of rural land. The experts classify this as suburban (knowing the context) and give it a score of being medium or low. The Fuzzy Urban Index rule will always score it with the lowest membership since the rule weighs the natural vegetation highly. Our future Fuzzy Urban Index efforts will focus on developing better rules to address complexities on the ground to reduce the impact of these errors. In addition, newer datasets of high resolution LIDAR imagery may result in better classification.

Experts were also asked to denote their level of confidence in scoring the 100 sites. The confidence levels are rated from 1 to 5. Five indicates the most confidence while 1 indicates the least confidence. In general, experts are fairly confident in terms of their validation. Experts are more correct in terms of class accuracy when they are very confident (5) about their ratings while errors happen when expert confidence drops to 4 and below (see Fig. 10).

5. Discussion & conclusion

This paper presents the development and implementation of a rule-based fuzzy expert system to characterize and map the spatial variation in urban class integrating a variety of data. We use an integrated CHANS framework to frame the problem and for linking human and natural sub-systems in urban regions. Such a framework enables a variety of perspectives to be embedded in one common framework. For example, Alberti's (2008) view of urban ecology as "the study of the ways that human and ecological systems evolve together in urbanizing regions" fits in this framework as does urban planning studies that design the environmental amenities with the goal to maximize social benefits (Pickett et al., 2011). Finally, the metaphor of urban metabolism has been used to research flows and transformations of energy and materials through cities (Hutyra et al., 2011), but metabolism is a state

Table 3
Comparing traditional land use categories and Fuzzy Urban Index by county.

County	Land use					Urbanness				
	Commercial	Highly built	Medium built	Low built	Veg.	VHigh	High	Medium	Low	VLow
Essex	6.07%	12.50%	7.90%	5.74%	67.80%	2.85%	8.33%	18.61%	15.92%	54.29%
Middlesex	8.22%	12.75%	10.98%	8.75%	59.30%	4.99%	8.79%	21.10%	23.30%	41.82%
Norfolk	7.18%	9.09%	13.17%	9.52%	61.04%	2.79%	7.87%	22.67%	23.28%	43.38%
Plymouth	3.87%	3.91%	5.64%	16.56%	70.01%	0.78%	2.60%	15.26%	26.11%	55.25%
Suffolk	25.89%	47.86%	6.09%	0.76%	19.40%	30.03%	24.76%	18.19%	5.94%	21.09%
Worcester	6.56%	3.35%	7.42%	8.66%	74.01%	1.37%	3.59%	12.58%	21.82%	60.63%

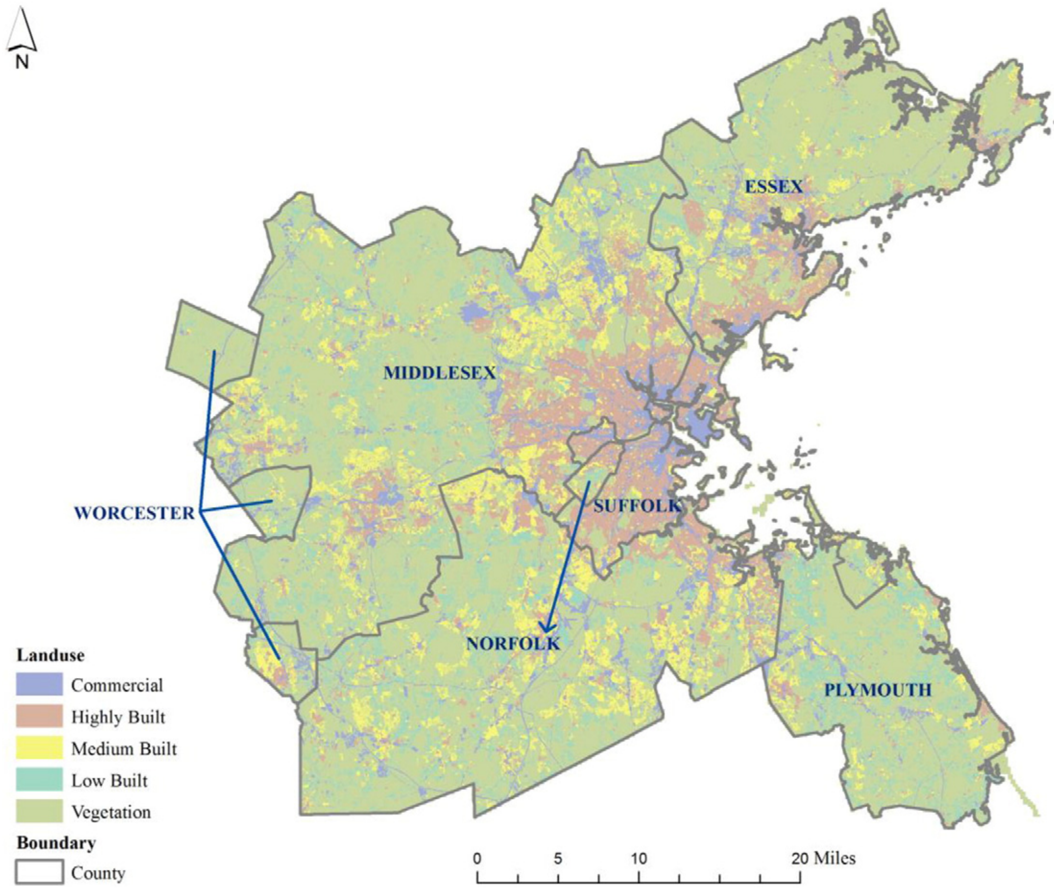

Fig. 8. Traditional land use map of Boston study area.

variable and does not indicate the nature of the spatial infrastructure or material and energy flows. Thus, an approach which defines the boundaries and spatial properties in which urban metabolism operates would advance the utility of that metaphor (Hutyra et al., 2011). These studies demonstrate that researchers are increasingly adopting an integrated approach to characterize urban landscapes and processes. The proposed metric called Fuzzy Urban Index will help in this research context in formulating simple rules using a fuzzy inference model. We can quantify the degree of urban characterization in the resultant map based on fuzzy memberships. The map enables us to visualize the heterogeneous characterization of the urban landscape impacted by the diverse inputs including population, land use, vegetation, and traffic volumes.

We illustrate the flexibility and utility of the Fuzzy Urban Index approach using a case study of the Boston Metro region using five inputs and eighteen rules. Rules used in this methodology are simple and help to define five levels of urban characterization. The resulting map from the Fuzzy Urban Index was validated using expert fuzzy ratings of 100 sites. The fuzzy model has 78.9% accuracy validated using Zadeh Max metric and substantially reduced accuracy using Zadeh Min. Our analysis of errors suggests that there are marked differences in expert ratings in areas of the map characterized as *medium* rating. This is not surprising given that ES tended to have strong agreement in *very high*, *high*, *very low fuzzy* urban ratings. Experts were asked to

Table 4
Zadeh Max and Min accuracy.

Class	Fuzzy Accuracy	
	Max (μ_S)	Min (μ_I)
Very low	80.0%	55.0%
Low	75.0%	40.0%
Medium	61.5%	30.8%
High	100.0%	53.3%
Very high	89.5%	42.1%
Overall	77.9%	46.8%

Fig. 9. Analyzing the differences between Fuzzy input and output functions.

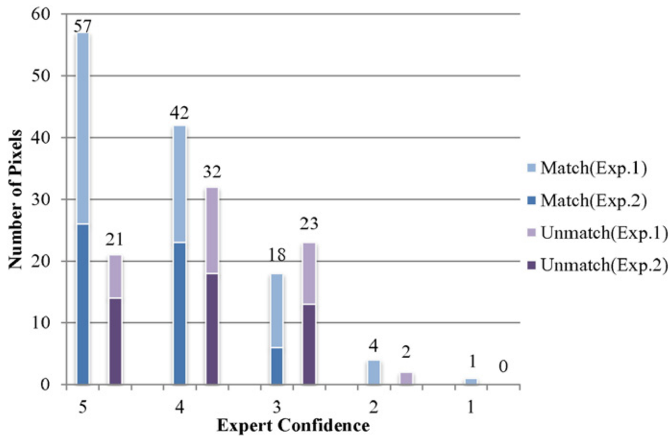

Fig. 10. Distribution of matches and mismatches for five levels of confidence.

assign a confidence rating for each of their ratings. Higher class accuracies resulted when experts were more confident in their ratings. Mismatches happened while experts were less confident. In addition, errors occur due to lack of rules in a specific context. The existing database of Fuzzy Urban Index rules could not label areas with high amount of flat, impervious surface with less population, such as parking lots and airports. Hence, Fuzzy Urban Index methodology resulted in errors in these locations. A better definition of these fuzzy urban classes can help overcome this limitation and will be further investigated in future studies.

Most inputs used in this study of Boston are readily available for any US city. However, the Fuzzy Urban Index framework is flexible enough to incorporate more inputs and rules to study urban systems based on CHANS framework. For example, the model can be customized with more inputs including household emission, carbon sequestration and soil respiration related to evolving themes in urban research related to urban sustainability and carbon balance in urban ecosystems (Müller & Burkhard, 2007). Rules can be generated to model urban metabolism using the Fuzzy Urban Index methodology.

Our future research would involve developing and comparing the same set of rules in other US cities such as Phoenix, Syracuse or Los Angeles, that are part of the ULTRA (Urban Long Term Research Area) network. Our long term goal is to provide a fuzzy inference decision tool system that would enable users to upload their input data, customize the rules and produce maps for a variety of specific research objectives. The integrated, multidisciplinary nature of our project maximizes opportunities to advance understanding of coupled natural and human systems in the urban context.

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