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Differentiating Urban Forms: A Neighborhood Typology for Understanding Urban Water Systems

With rising populations and changing climates, urban areas need water systems capable of meeting a range of social, economic and environmental sustainability objectives. Different configurations of urban growth and development also produce varying water system outcomes. In this paper we develop a multi-dimensional classification scheme that identifies distinct configurations of 'urban forms' in Northern Utah, USA. We identified characteristics within urban landscapes that have been linked in the scientific literature to three types of water outcomes: water demand, water budgets, and water quality. Using publicly-available data at the census block scale, we create a typology of urban neighborhoods that share distinctive combinations of natural, built, and social structures that are expected to shape water system dynamics. The resulting typology provides a conceptual and empirical basis to generate hypotheses and design studies of complex urban water systems. We illustrate the value of the typology by using data from surveys of urban residents. While our typology classifications are unique to this region, the methodology relies on publicly available data and could be replicated in other urban areas.

Keywords

urban hydrology, urban ecology, urban landscapes, cluster analysis

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INTRODUCTION

Rapid population growth, aging infrastructure, and changes in climate have generated a host of water-related challenges for cities across the globe. These challenges include difficulties projecting or meeting urban water demand, managing wastewater, addressing the impacts of urban runoff on water quality, and understanding the broader effect of urban development on local and regional hydrology and ecosystems (Vorosmarty et al. 2000; Walsh 2000; Paul and Meyer 2001; Brabec et al. 2002; Kaushal et al. 2015; Li et al. 2015).

Urban areas, with high population densities and an extensive built environment, represent landscapes where human influences on biotic and physical systems are dominant (Alberti 2005; Pickett et al. 2011). However, the urban landscape can be extremely complex, and neighborhood differences in built, social, and natural environmental characteristics can cause different water demand, water quality, and ecohydrologic outcomes (Grove and Burch 1997; Cadenasso et al. 2007; Pickett and Grove 2009; Fullerton and Molina 2010; Jacobson 2011).

In this paper, we use principal components analysis and cluster analysis to generate a statistical typology of urban landscapes that captures diverse configurations of biophysical conditions, built environment, and social structure that have been linked in the literature to water outcomes. We utilize a form of geodemographic segmentation (Troy 2008) by using socially-constructed boundaries (census block groups) as the units of analysis to help capture the important role of social institutions, networks and historic residential settlement processes that shape the emergence and evolution of urban neighborhoods. The resulting typology of urban landscapes provides a conceptual and empirical basis to generate hypotheses and design studies of complex urban water systems. It also is explicitly designed to provide a guide to planners seeking to disaggregate the impacts of diverse patterns of urban growth and development on water resources and future water demand. In this paper we demonstrate the value of this typology in explaining variation in water attitudes and behaviors of urban residents. We also point to ways in which the typology could be used to structure the investigation of variable effects of urban forms on water quality and ecohydrology. While our typology represents a regional case study, and our specific findings are limited to Northern Utah, it utilizes a methodology and relies on publicly available data that would allow replication in other urban areas across the U.S.

Our paper seeks to advance or answer the following research questions:

i. What measurable attributes of urban neighborhoods have been linked in the scientific literature to a range of water outcomes (demand, quality, and ecohydrology)?

ii. To what extent do urban neighborhoods reflect distinctive combinations of these measurable attributes?

iii. Are urban neighborhood types systematically associated with resident water attitudes and behaviors?

iv. How can a formal typology of urban neighborhoods be used to guide the scientific study and practical management of urban water systems?

DEVELOPMENT OF A 'WATER-RELEVANT' URBAN NEIGHBORHOOD TYPOLOGY

Urban Water System Conceptual Model

Our approach to the study of coupled human-natural water systems is guided by the integrated Structure, Actor and Water (iSAW) framework (Figure 1; Hale et al. 2015). The iSAW conceptual framework builds on many previous efforts to represent the dynamic relationships between human and natural systems (Duncan, Schnore and Rossi 1959; Grove and Burch 1997; Wagener et al. 2010; Collins et al. 2011; Pataki et al. 2011; Sivapalan et al. 2014; Grove et al. 2015). The iSAW framework posits that coupled systems operate in structured contexts, and three elements of 'structure' – natural, built, and social – mediate relationships between human actors and water system outcomes across a range of scales. Natural structures include biophysical characteristics of the system including topography, climate, soils, natural vegetation, and other ecological components. Built structures in water systems are represented by patterns of human-altered land cover and landscaping, building types and arrangements, and constructed water infrastructure. Social structures reflect sociodemographic attributes of residents, cultural norms and values, and market, organizational, legal and policy contexts.

These structures interact with each other to enable or constrain people's decisions and behaviors and shape water quantity and quality outcomes. The iSAW model suggests that studies of urban water system dynamics must account for variation in natural, built and social structures. Our urban neighborhood typology is designed to provide a practical approach to mapping structural variation across the urban landscape.

Methodological Approaches to Landscape Classification

Systems for classifying natural landscapes according to combinations of biophysical characteristics and processes (natural structure) are common. For example, ecoregions have been defined based on combinations of topography, climate, and vegetative land cover (Thompson et al. 2004). The Bailey's Ecoregion classification system is a hierarchical scheme using data on climate (precipitation and temperature) to define physiographic divisions, which are then subclassified into provinces based on vegetation and land cover (Bailey 2004). Similarly, classification of soils within natural landscapes is often based on combinations of soil formation processes and soil texture (Albrecht et al. 2005). A major recent effort by the USGS and ESRI used climate, landform, geology, and land cover to classify 'ecological land units' globally (Sayre et al. 2014).

Many landscape classification systems include some consideration of human activities using measures of landcover (natural and built structure) and land use (a simple expression of social structure). Anderson et al. (1976) developed a popular classification scheme in which urban land uses are first distinguished from a range of natural forms of land cover (agriculture, forests, rangeland, etc.). Within urban areas, these classification systems then sometimes differentiate sub-classes based on population density or predominant type of urban land use (e.g., residential, commercial, etc.). Ellis and Ramankutty (2008) used global data for 5' grid cells (~87 km^2) on population density (urban, non-urban), land use, and land cover in a cluster analysis to identify 21 types of 'biomes', 18 of which were 'anthropogenic' (where human presence is a defining feature of the landscape). Duany and Talen (2002) characterized 'urban ecozones' based both on the level and intensity of 'urban character' (population density, impervious surface area, street networks) and a set of distinctive biophysical and ecological properties. Cadenasso et al. (2007) developed the High Ecological Resolution Classification for Urban Landscapes and Environmental Systems (HERCULES) methodology to classify urban ecosystems in Baltimore, Maryland, USA based on the integration of information about natural and built structures with a focus on measures of urban land cover that capture building types, surface materials, and vegetation. They demonstrate how differentiation of urban areas based on these attributes better explain environmental outcomes (like nitrogen export) than conventional categorizations that rely only on land use.

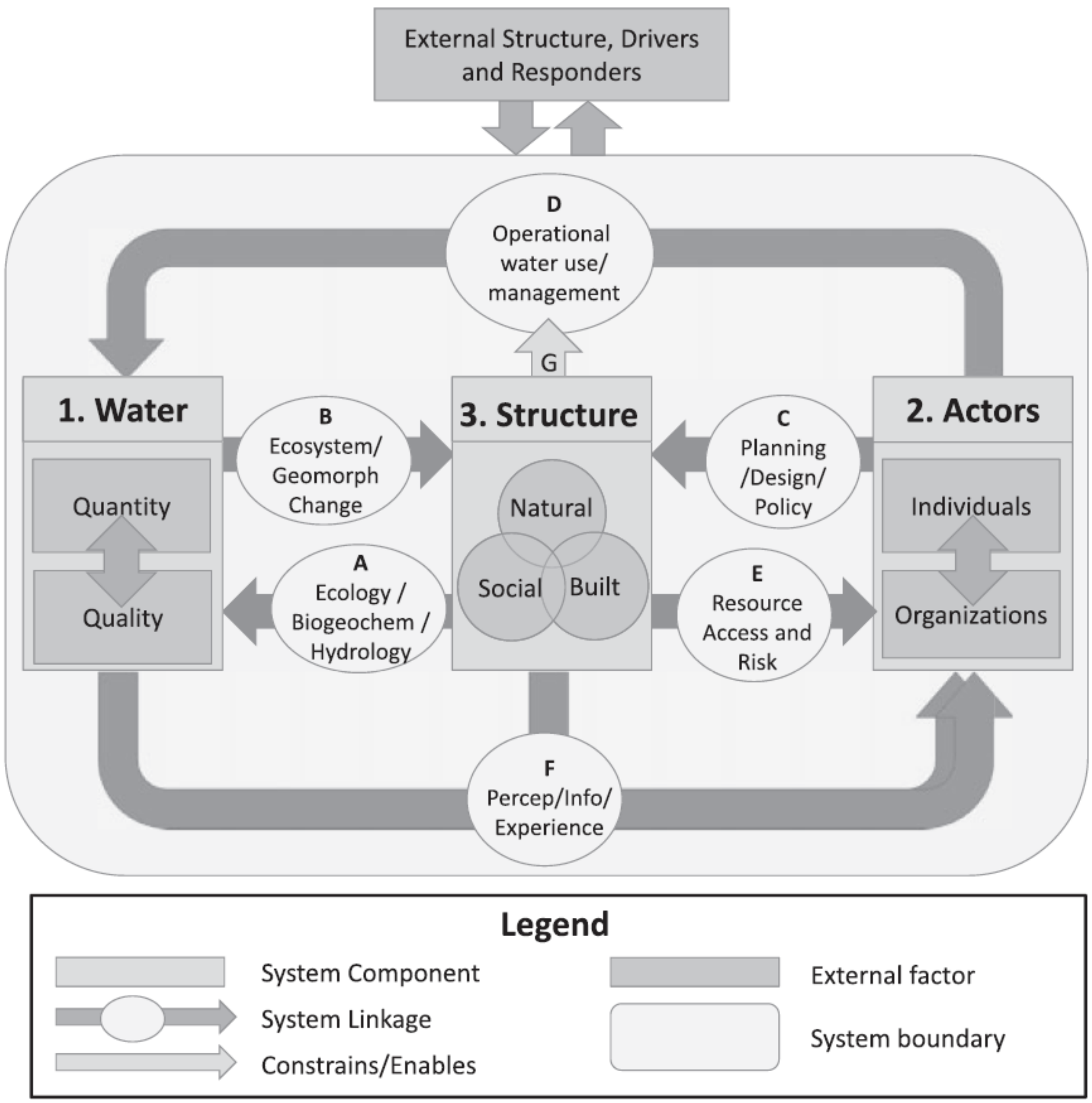

Figure 1 The integrated Structure-Actor-Water (iSAW) framework (Hale et al. 2015).

Not many scholars have classified landscapes with a particular focus on water issues. Hutchinson et al. (2010) created a national typology of 12 'Human Impacted Water Environment Classes' using cluster analysis of measures of climate and physical geography (natural structure), land cover (built structure) and population density and patterns of water use (social structure) at the HUC-8 scale (~500,000 ha watersheds) across the continental U.S.

While natural and built structures in the urban environment have received the most attention, there are a few examples of landscape classifications that have integrated sophisticated measures of social structure. However, socially-meaningful units of analysis in urban space, such as households, neighborhoods, and communities, can be as important in driving human decisions and behaviors as natural or biophysical features like watershed catchments (Hawley and Duncan 1957). This is partly because natural watershed boundaries (and patterns of surface water flows) are often significantly disrupted in urban landscapes due to the impacts of built infrastructure (roads, buildings, water distribution networks, wastewater systems, and stormwater management structures). Additionally, variation in water use, vegetation/landscaping, and management of the water infrastructure is shaped by social actors (individuals and organizations) that act within domains of influence in socially-defined geographic areas.

Grove and Burch (1997) made the case for integrating social and ecological factors when differentiating space within urban landscapes, though they did not propose a systematic method to implement this idea. Later, Grove et al. (2006a, 2006b) used commercially available data on consumption patterns (developed for marketing firms) at the census block scale to demonstrate that distinctive social and demographic characteristics of neighborhoods were strong predictors of vegetation patterns across a major urban area (see also Boone et al. 2010). Nielsen-Pincus et al. (2015) classified land-owners in the wildland-urban interface of Oregon's Williamette Valley Ecoregion at the parcel scale on the basis of lifestyle motivations, land management behaviors, real estate properties, and land cover. A growing body of social science research suggests that sociodemographic attributes of individuals, households, and neighborhoods are strong predictors of behaviors that can shape water system outcomes (summarized below). In sum, studies of water within urban landscapes should at minimum capture information about configurations of natural (biophysical, climate, land cover), built (roads, buildings, parcels, and infrastructure), and social (population density, land use, sociodemographic, and institutional) structural characteristics (Pickett and Grove 2009).

Water-Relevant Characteristics of Urban Landscapes

Our typology is guided by scientific literature that identifies a number of key natural, built, and social structural attributes of urban landscapes that influence three types of water system outcomes: water use, water quality, and ecohydrology. In this section we present a brief overview of some of the findings from previous research that shaped our selection of variables to use in our statistical analysis. While empirical results presented below will focus on water use, the variables used in creating the typology were designed to allow the resulting classifications to be a basis for structuring studies of the impacts of urban form on water quality and ecohydrologic outcomes.

Water Use

A growing literature links different urban configurations of natural, built, and social environments to patterns of residential and commercial water use. In a recent literature review, House-Peters and Chang (2011) found that climate, land cover (vegetation mix), built environment (parcel and housing mix and size), demographic characteristics (age, income, education, household size), and policy context (water pricing structure) were all linked to patterns of water use at diverse temporal and spatial scales. Other researchers have demonstrated strong relationships between water use and different forms of residential housing and vegetative cover (Aitken et al. 1994; Troy et al. 2005; Balling 2007; Guhathakurta 2007; Zhou et al. 2009; Blokker et al. 2010; Polebitski and Palmer 2010). Specifically, housing type and size (Troy et al. 2005; House-Peters and Chang 2011; Stoker and Rothfeder 2014), housing age (Grove et al 2006b), and ownership status (Mee et al. 2014) have all been linked to both landscaping choices and water use behaviors. Neighborhood-specific norms of landscaping and water use behavior can influence individual water actor decisions (Larson and Brumand 2014).

Aspects of the built water environment such as road and parcel configurations can affect parcel sizes and water use (Chang et al. 2010; Guhathakurta and Gober 2010). In many cities, substantial gains in water conservation can be achieved by fixing leaky pipes. As a result, there are urgent calls to upgrade and repair aging infrastructure that is used to distribute water to customers across the U.S. (Grigg 2005). Differences in regional climate clearly affect regional variations in water demand (Balling 2007; Guhathakurta 2007; Endter-Wada et al. 2008), while microclimates related to elevation, topography, proximity to open space, or the impacts of urban heat islands can explain variation in parcel-scale water use (Whitlow et al. 1992; Nouri et al. 2013).

Water Quality

Urbanization processes have long been linked to ‘urban stream syndrome’ in which ecological functions in streams draining urban areas are systematically degraded (Walsh et al. 2005). Nitrate, phosphate and sediment pollution from urban runoff are greatly influenced by built structures, particularly impervious surface area, landscape plant composition and irrigation systems, and stormwater drainage infrastructure (Brabec et al. 2002; Hatt et al. 2004; Yang and Li 2013). Effects of natural structures (like topography, climate and land cover) on urban water quality can vary depending on the scale at which they are measured (Sun et al. 2014). Cadenasso et al. (2007) demonstrated how neighborhood characteristics (land use, population density, and built infrastructure) explain more variation in rates of nutrient export from diverse urban subwatersheds than many traditional natural structure variables. Finally, variation in landscaping and irrigation choices that impact water quality have been linked to aspects of social structure, including socioeconomic status, race/ethnicity, local social organizations, and governance institutions (Larson et al 2009; Cook et al. 2012; Fraser et al. 2013).

Ecohydrology

Ecohydrology is the study of the partitioning of fluxes between groundwater, surface, and atmospheric pathways, and the interactions of hydrology with ecological processes (Rodriguez-Iturbe 2000). Urban environments significantly affect hydrologic processes and sediment flows because of changes in impervious surface area (Paul and Meyer 2001; Alberti 2005; Walsh et al. 2005). Areas with more imperviousness experience reduced infiltration and accelerated runoff (Sanders 1986), though the effects may be non-linear (Dunne and Leopold 1978). Variation in the type, density, and spatial configuration of landscape vegetation not only affects the rate of infiltration and runoff, but also alters the amount and timing of evapotranspiration in urban landscapes (Jenerette et al. 2013; Zhou et al. 2014). Configurations of natural structures (natural vegetation and riparian and wetland area conditions) and how those are altered in the urbanization process also have implications for hydrologic function (Brody et al. 2007; Brabec 2009).

METHODOLOGY

Study Area

Our project develops a typology of neighborhoods for the greater Wasatch Range Metropolitan Area (WRMA), a nearly continuous area of urbanized land running north and south for approximately 260 km along the Wasatch Mountain Range in Northern Utah. The WRMA is home to nearly 2.3 million residents and includes numerous incorporated municipalities ranging in size from a few thousand to nearly 200,000 people in Salt Lake City (the state capital). A relatively young population and high fertility rates contribute to a projected doubling of the population by 2050 (UDWR 2012).

WRMA urban areas vary across different *biophysical environments* – ranging from the original nineteenth century Anglo-European settlements at the canyon mouths where perennial streams provide water from mountain snowpack, to warmer and dryer bottomlands of Basin and Range valleys shared by irrigated agriculture and new suburban homes, to the colder and wetter higher elevation mountain benches and valleys where more expensive residences, second home developments, and recreational resorts are concentrated. These urban areas also comprise a heterogeneous stock of *built environments*, including traditional residential neighborhoods with aging water infrastructure built in the early twentieth century, dense urban commercial and industrial zones, rapidly-expanding suburban areas dominated by single-family homes, multi-family townhouse developments, downtown condominiums and apartment complexes, and new residential and commercial development replacing recently irrigated agricultural lands at the urban fringe. Finally, these urban areas include diverse *social environments* that reflect the distinctive demographic, economic, cultural and policy forces that shape patterns of urban migration, settlement and land conversion.

Water resource management is a prominent challenge in this region (Burnham et al. *in press*). Utah ranks near the bottom in the U.S. in state-wide annual precipitation, but per-capita domestic water use is among the highest in the nation (Maupin et al. 2014). Most municipal and industrial water use in Utah is for outdoor irrigation (UDWR 2010b), and the regional water supply relies on a combination of groundwater wells, springs, and reservoirs in nearby mountains (U.S. EPA 2010). Urban water demand is expected to soon outstrip this supply system in many areas (UDWR 2014).

Identifying 'Neighborhoods'

Our analysis sought to differentiate configurations of neighborhoods within the urbanized areas of the WRMA. Selecting an appropriate boundary for neighborhoods is a persistent problem that challenges studies of housing markets (Clapp and Wang 2006), urban planning (Horner and Murray 2002), and other social sciences (Sampson et al. 2002). Moreover, decisions about the scale at which neighborhoods are operationalized can affect the patterns we observe (Dark and Bram 2007; Wong 2009).

While imperfect in many respects, census blocks (often similar to a city block) are the finest scale geographic area at which demographic information is released by the U.S. Bureau of the Census, which makes them particularly useful for large scale studies that require statistical data on neighborhood characteristics. Census block groups (CBGs) represent clusters of census blocks that follow local roads, natural features, or political boundaries and often (but not always) approximate neighborhood boundaries recognized by local residents. As a result, similar to previous urban water- and ecosystem-related research (Grove et al. 2006a; Shay and Khattak 2007; Chang et al. 2010; House-Peters et al. 2010; Larson et al. 2013), we utilized the CBG as the unit of analysis for our project.

Our analysis includes urban or urbanizing areas within the WRMA that have residential population densities greater than 38.6 persons per km^2 (100 persons per mile^2), a conservative threshold below which areas are generally defined as exurban and in the process of urbanizing (Clark et al. 2009) but are clearly not yet urban (Clark et al. 2009). To capture areas that are in the process of transitioning to urban density in this rapidly changing landscape, we used a threshold that is lower than the U.S. Bureau of Census' official definition of 'urbanized areas' and 'urban clusters' (1,000 and 5,000 persons per mile^2, respectively; Bureau of Census 2011). Moreover, because some CBGs in the WRMA region contain significant areas of federally-owned land and open water (notably portions of the Great Salt Lake), we calculated population density using 2010 CBG population counts divided by the area of non-federal land *excluding* open water (a form of dasymetric mapping – see Mennis 2002 and Boone 2008).

The 10-county WRMA contains a total of 1,457 CBGs, of which 1,384 had population densities above our threshold. These urban CBGs contain 96 percent of the study area's total population, but represent just 8 percent of the overall land area (and 14 percent of the non-federal land area). The median size of CBGs included in the analysis was 0.9 km^2.

Attributes of Neighborhoods

To construct our typology, we used publicly available data to capture aspects of natural, built, and social structure that have been linked to urban water use, water quality, and ecohydrology. The 47 variables used in this analysis are aggregated at the census block group level for all urban CBGs in the WRMA. Descriptions of the key measures are summarized below, but full technical details and sources of data can be found in (Supplemental Tables A and B and in *self-reference omitted*).

Natural Structure

To capture the effects of neighborhood scale microclimate, we computed average summer and annual temperature and precipitation for the period 2010-2012 (using data from the PRISM Climate Group), and mean elevation for each CBG (from the USGS National Digital Elevation Map dataset).

Built Structure

Indicators of build structure include land cover/landscaping, housing density, road and parcel configuration, and access to a public water supply. We used three measures of land cover, each derived from remotely sensed imagery: percent impervious surface area (using the 2006 National Land Cover Database, itself produced from 30m Landsat imagery), percent tree cover (from 250m MODIS Vegetation Continuous Fields data; VCF), and greenness (using Landsat-derived Normalized Difference Vegetation Index at 30m resolution from 2006 and 2007). For each measure, we computed the mean value across all pixels using the ArcGIS 10.1 Zonal Statistics geoprocessing tool. We estimated housing density with two measures: a) *overall housing density* for the entire CBG land area, excluding federal lands and open water; and b) *residential housing density* to reflect the actual density within the subarea that is in residential land use. We used publicly-available parcel and road network data to calculate mean and median parcel size for each CBG, as well as four measures of street configurations: average block length, median block length, intersection density, and percent of intersections that are four-way stops. Because access to a public culinary water supply affects water use (UDWR 2010a), we calculated the percent of parcels served by a public water supplier.

Social Structure

Variations in social structure are captured with indicators of land use, housing characteristics, and individual and household demographics. Using parcel-scale land use classifications from the 2010 Utah Water Related Land Use (UWRLU) dataset developed by the Utah Division of Water Resources (UDWR 2013), we estimated percent land area within each CBG in six mutually exclusive categories: residential, commercial/industrial, urban open and green space, farmsteads, irrigated agriculture, and non-irrigated agriculture. From the same data we calculated an overall measure of land use diversity using the inverse Gini-Simpson entropy index (Simpson, 1949). This index represents the weighted arithmetic mean of the proportional abundances of the types of interest, and large values represent situations where diversity of two housing types is greater. Technically it is a measure of entropy and performs best when the number of different categories is relatively small (Jost 2006). We also combined data from ESRI's online vector database and a state database to calculate percent land area that is managed as a local, city, or state park.

Following the example of Grove et al. (2006b), we used U.S. Census data to calculate several indicators of housing characteristics. These included: a) percent vacant housing units, b) percent renter-occupied units, c) percent detached single-family homes, d) percent of housing built since 1990, e) median year structures were built, f) median number of rooms per housing unit, g) median housing value, h) percent mobile homes, and i) diversity of building housing types (calculated using the Gini-Simpson entropy index described earlier).

We use ten measures, also from U.S. Census data, to describe the aggregate demographic attributes of households and individuals in each CBG: a) overall population density; b) natural log of residential population density; c) median age; d) percent over 65 years old; e) percent non-Hispanic white; f) percent adults with BS or higher educational attainment; g) percent with household income over $100,000; h) median household income; i) per capita income; and j) poverty rate. We use three measures to capture variation in household characteristics at the CBG level: a) mean household size; b) percent family households; and c) number of working adults per household.

Factor Analysis

We used factor analysis with principal components extraction and orthogonal rotation (SPSS v21) to reduce the 47 input variables to a smaller set of factors that capture underlying attributes of census block groups. Factor analysis examines patterns of correlations among the different input variables and extracts uncorrelated statistical dimensions that each explain a proportion of the observed variation in the data (e.g., the first principle component selected in the analysis will explain the highest variance and each successive factor will be the orthogonal dimension that explains the next most variance (Thompson 2004). Our factor analysis identified a set of 9 distinct factors with eigenvalues over 1 that together explained 76.4 percent of the variation among the 47 observed variables (Table 1).

A brief description of each factor is included below.

- *FACTOR 1: Housing Mix – Suburban (λ=8.4; 17.9% variance explained).* The housing mix-suburban factor describes how strongly neighborhoods display the characteristics of typical suburban residential neighborhoods. High values represent neighborhoods with a high percentage of single-family homes, low levels of housing diversity, few renters, larger houses and more people per household. These neighborhoods also have relatively low population density, higher household income, and low poverty rates.
- *FACTOR 2: Microclimate (λ=4.9; 10.4%).* High scores on the elevation/climate factor describe neighborhoods with higher elevation, cooler temperatures, and greater precipitation. These are also places that have significant amounts of vacant housing and greater tree cover, which are typical of mountain second home developments in this region.
- *FACTOR 3: Land Use Diversity – Non-Residential (λ=4.7; 10.0%).* Neighborhoods scoring high on this factor have high diversity of land uses and a relatively low fraction of land in residential uses. These places also tend to have lower population and housing density, less tree cover, and significant areas of non-irrigated agriculture or commercial and industrial land uses.
- *FACTOR 4: Socioeconomic Status (λ=4.2; 9.0%).* High scores on the Socioeconomic Status (SES) factor typify neighborhoods that have a relatively large percentage of adults with at least a BS degree, higher median housing values and per capita incomes, and a greater percentage of households with incomes above than $100,000. Neighborhoods with higher SES scores in this area also have less racial or ethnic diversity.

- *FACTOR 5: Low Density Settlement (λ=4.2; 8.9%).* High scores on this factor describe neighborhoods that have large parcel and block sizes. These tend to be places that are less likely to be served by a public water supplier. A map of this factor suggests that it captures areas on the exurban fringes of the WRMA.
- *FACTOR 6: Population/Housing Age (λ=3.3; 7.1%).* High scores on this factor describe neighborhoods that have a relatively young population, large household sizes, and a high percentage of housing built since 1990, as well as a high (recent) median year built. One interesting finding is that age of population and age of housing stock are positively correlated in Utah; younger populations tend to live in more recently-built housing.
- *FACTOR 7: Irrigated Agriculture and Greenness (λ=2.6; 5.6%).* This factor describes neighborhoods that are relatively dominated by vegetation. High values are associated with relatively high NDVI scores, a greater fraction of land in irrigated agriculture and farmsteads, and smaller fraction of impervious surface area or commercial and industrial land uses.
- *FACTOR 8: Urban Parks and Open Space (λ=2.0; 4.3%).* High scores on this factor describe neighborhoods that have a high percentage of land in urban open space and parks.
- *FACTOR 9: Mobile Homes (λ=1.6; 3.4%).* The mobile homes factor describes neighborhoods with a relatively large percentage of housing units that are mobile homes, more recently-built housing stock, fewer four-way intersections and shorter median block lengths.

Table 1 Factor loadings for all 47 variables used in analysis *(only loadings greater than +/- 0.3 are shown; largest loading for each variable in bold)*.

	Factors								
	Housing Mix: Suburban	Micro-Climate	Land Use Mix: Non-Residential	Socio-economic Status	Low Density Development	Population-Housing Age	Land Cover: Greenness	Urban Parks and Open Space	Mobile Homes
Eigenvalue	8.4	4.9	4.7	4.2	4.2	3.3	2.6	2.0	1.6
Percent of Variance Explained	17.8	10.4	10.0	9.0	8.9	7.1	5.6	4.3	3.4
% Detached SF Homes	**0.933**								
% Renter Occupied	**-0.896**								
Diversity of Housing Types	**-0.888**								
% Family Households	**0.858**								
Median # Rooms	**0.842**			0.375					
Log of Residential Housing Density	**-0.736**						-0.437		
Mean Household Size	**0.694**					0.613			
Poverty Rate	**-0.611**								
Log of Residential Pop Density	**-0.569**						-0.502		
Employed Adults Per Household	**0.557**								
Average Summer Max. Temperature		**-0.930**							
Average Annual Temperature		**-0.888**							
Mean Elevation		**0.797**		0.331					
Average Annual Precipitation		**0.784**							
Average Summer Precipitation		**0.748**							
% Vacant Housing Units	-0.447	**0.549**							
% in Residential Land Use			**-0.834**		-0.359				
Land Use Diversity Index			**0.776**						
Overall Population Density	-0.379		**-0.768**						
Intersection Density			**-0.718**		-0.319				
Overall Housing Density	-0.579		**-0.659**						
% Land In Non-Irrigated Agriculture			**0.483**			0.326			
% Tree Cover		0.389	**-0.460**	0.384		-0.324			
% Adults with BS or Higher Education				**0.818**					
Median Housing Value				**0.805**					
Per Capita Income		0.319		**0.744**		-0.342			
% Households with Income > 100K	0.509			**0.738**					
Median Household Income	0.627			**0.649**					
% Non-Hispanic White	0.348			**0.528**			0.394		
Median Parcel Size					**0.812**				
Average Block Size					**0.801**				
Average Parcel Size					**0.785**				
Median Block Size					**0.778**				-0.344
% Parcels Served By Public Supplier					**-0.774**				
% Over 65						**-0.861**			
Median Age						**-0.826**			
% Housing Built Since 1990			0.445			**0.588**			0.308
Median Year Structure Built			0.390			**0.537**			0.489
Greenness (NDVI)							**0.620**		
% Commercial/Industrial Land Uses	-0.504		0.458				**-0.582**		
% Land In Irrigated Ag			0.365		0.424		**0.568**		
% Impervious Surface	-0.422	-0.339	-0.355		-0.325		**-0.513**		
% Land In Farmsteads					0.319		**0.500**		
% Land In Open Space								**0.944**	
% Land In Urban Parks								**0.936**	
% Four-Way Intersections									**-0.668**
% Mobile Homes				-0.302					**0.624**

Cluster Analysis

We then used the factor scores from the top eight factors[1] as input data in a hierarchical cluster analysis to group CBGs into 'neighborhood types'. Cluster analysis uses measures of statistical similarity or distance to combine diverse units of analysis (census block groups in our case) into sets that are as homogenous as possible within each cluster, and as different as possible between the clusters (Anderberg 1973). Similarity is measured in terms of communalities that reflect statistical distance between individual members and the aggregated clusters (Kaufman and Rousseeuw 1990). We used the SPSS v21 CLUSTER procedure, a hierarchical clustering that utilizes a squared Euclidean distance measure based on within-group average linkages. The process initially treats each individual case as a separate cluster, then sequentially combines them into new clusters based on identifying the merger that produces a group with the smallest within-group average distance scores across the 8 input factors. The process repeats iteratively until all cases are included in a single cluster.

A variety of techniques can be used to determine the number of clusters that represent the optimal balance between the goals of within-cluster homogeneity, between-cluster heterogeneity, and overall parsimony (e.g., a tractable number of cluster groups). Before conducting the analysis, we set a maximum of 50 clusters and examined the merger dendogram and agglomeration schedule for the last 50 iterations of clustering to see where natural break points could be identified (e.g., where statistical indicators of distance suggested that relatively unlike clusters were being forced to merge at a given step). Based on an evaluation of the cluster distance scores and a visual assessment of the dendogram associated with the final stepwise clustering mergers, we identified several points where additional clustering would more dramatically reduce internal coherence within the clusters than previous mergers (Supplemental Figure A). Using this information, we selected two cutoffs for our analysis.

First we determined a more thematically resolved set that included 32 individual clusters: we refer to these as Neighborhood Types (NTs). A coarser aggregation of 10 major neighborhood clusters was also defined, with each of the 32 NTs being nested within one of these 10 major clusters (hereafter Cluster Groups, or CGs). Two of these 10 major CGs and 14 of the NTs had ten or fewer CBG members and were dropped from further discussion since they represent outliers that did not fit with many other cases and forcing them into a cluster group or neighborhood type would reduce the internal coherence of those categories. Overall, nearly 98 percent of CBGs were classified into a CG and an NT.

[1] The ninth factor (mobile homes) was not used as input to the cluster analysis because it explained little variance and generated clusters that were somewhat less consistent with locally recognized neighborhood types.

RESULTS

This analytic approach identified 8 major CGs and 18 associated NTs across the nearly 1,400 census block groups with population densities over 100 persons per square mile in Northern Utah. Each CG (and NT) was given a specific descriptive name that reflects its defining attributes (Table 2).

Major Cluster Groups

The 8 major CGs each account for 6 to 20 percent of the population and 2 to 27 percent of the urban land area in the WRMA region. The defining attributes for each cluster group and neighborhood type (mean scores on the 8 factors; Figures 2a and 2b) and map of cluster results (Figure 3) show how the urban landscape can be differentiated into substantively meaningful subareas from the perspective of human/natural water systems. Based on our interactions with researches, urban planners, and elected officials since the development of the typology, the cluster groups appear to capture boundaries and regions that are consistent with many stakeholder recognized neighborhood boundaries within our larger metropolitan study area. Below we present more detailed descriptions and profiles of the major CGs and individual NTs.

Housing Type and Land Use Patterns

Different mixes of housing types and land uses serve to distinguish most of our neighborhood types. Mean factor scores on two key factors – Housing Mix-Suburban (Factor 1) and Land Use Diversity-Non-Residential (Factor 3) – are important drivers of classification into the cluster groups. Three major CGs – New Suburban, Suburban Working Class, and Moderate Middle – are notable for unusually high scores on the Housing Mix-Suburban factor. This reflects a greater predominance of single-family homes, less diversity in housing types, larger household sizes, lower overall housing density, and fewer renters. At the same time, two other CGs –Mixed Urban Residential and Urban Scene –have unusually low scores on that same factor. These places have more non-family housing, greater housing diversity and density, and smaller housing units.

Two CGs – Expanding City and Urban Scene – are also distinguished for having high scores on the Land Use Diversity - Non-Residential factor, which captures situations with greater land use diversity and lower proportions of residential land use. Interestingly, these CGs appear at both extremes of urban development. The first consists of three NTs at the urban fringe that all have significant areas of agricultural or undeveloped land uses. The second reflects three NTs that are located in highly urbanized downtown areas with a greater amount of commercial and industrial land uses. Finally, three major CGs – Suburban Working Class, Moderate Middle, and Mixed Urban Residential neighborhoods – share notably low scores on the Land Use Diversity-Non-Residential factor. In these neighborhoods, one finds less land use diversity, a greater share of land used for housing, and higher population densities

Table 2 Major urban cluster groups and neighborhood types in WRMA.

CLUSTER GROUP (CG) *Description*	***Neighborhood Type (NT)***	**N CBGs**	**Percent Pop.**	**Percent Area**[1]
EXPANDING CITY		**168**	**14.5%**	**27.2%**
High land use diversity, low overall residential land use, large lots, lower elevation; irrigated farms	*Mature Homesteaders*	*91*	*7.5%*	*13.6%*
	Young Homesteaders	*60*	*5.8%*	*7.4%*
	Green Acres	*17*	*1.3%*	*6.2%*
NEW SUBURBAN		**228**	**20.4%**	**19.8%**
Single-family homes, low levels of housing diversity, newly built houses, family households, younger populations, smaller lot sizes	*Starter Suburbs*	*124*	*10.6%*	*6.7%*
	Away-from-it-all Suburbs	*47*	*5.1%*	*7.4%*
	Suburban Elite	*47*	*4.1%*	*3.5%*
	Other	*10*	*0.5%*	*2.2%*
SUBURBAN WORKING CLASS		**100**	**7.5%**	**9.1%**
Single-family homes, family households, younger, low green land cover, moderate to low SES.	*Working Class Suburban*	*99*	*7.5%*	*8.4%*
	Other	*1*	*0.0%*	*0.8%*
MODERATE MIDDLE		**224**	**14.4%**	**17.0%**
Residential land use, family households, older housing and populations.	*Working Class Trad.*	*112*	*7.2%*	*5.8%*
	Middle Class w/ a View	*106*	*6.8%*	*7.6%*
	Other	*6*	*0.4%*	*3.6%*
TRADITIONAL RESIDENTIAL		**281**	**17.4%**	**11.1%**
Older housing stock, smaller lot sizes, lower elevations.	*Original Residential*	*131*	*7.4%*	*3.7%*
	Traditional Upper Crust	*146*	*9.8%*	*5.7%*
	Other	*4*	*0.2%*	*1.7%*
PARKSIDE RESIDENTIAL		**87**	**5.7%**	**3.0%**
Predominantly residential, but contains significant urban park and open space areas.	*Neighborhood Park*	*70*	*4.7%*	*2.5%*
	City Park	*12*	*0.6%*	*0.4%*
	Other	*5*	*0.4%*	*0.2%*
MIXED URBAN RESIDENTIAL		**137**	**9.2%**	**1.9%**
Dominated by residential land use, but non-suburban character, diverse housing mix, non-family households, young.	*Working Class Mixed*	*70*	*5.2%*	*1.2%*
	Wasatch Bohemians	*62*	*3.7%*	*0.6%*
	Other	*5*	*0.3%*	*0.1%*
URBAN SCENE		**127**	**8.7%**	**7.0%**
Diverse land use, non-residential land use, mixed housing, low green landcover.	*Downtown Residential*	*75*	*5.1%*	*2.3%*
	Downtown Industrial	*36*	*2.5%*	*3.7%*
	Downtown Commercial	*15*	*1.0%*	*0.9%*
	Other	*1*	*0.1%*	*0.1%*
Unclassified CBGs		**32**	**2.1%**	**3.9%**
TOTAL		**1,384**	**100.0%**	**100.0%**

Figure 2a Mean factor scores by cluster groups and neighborhood types.

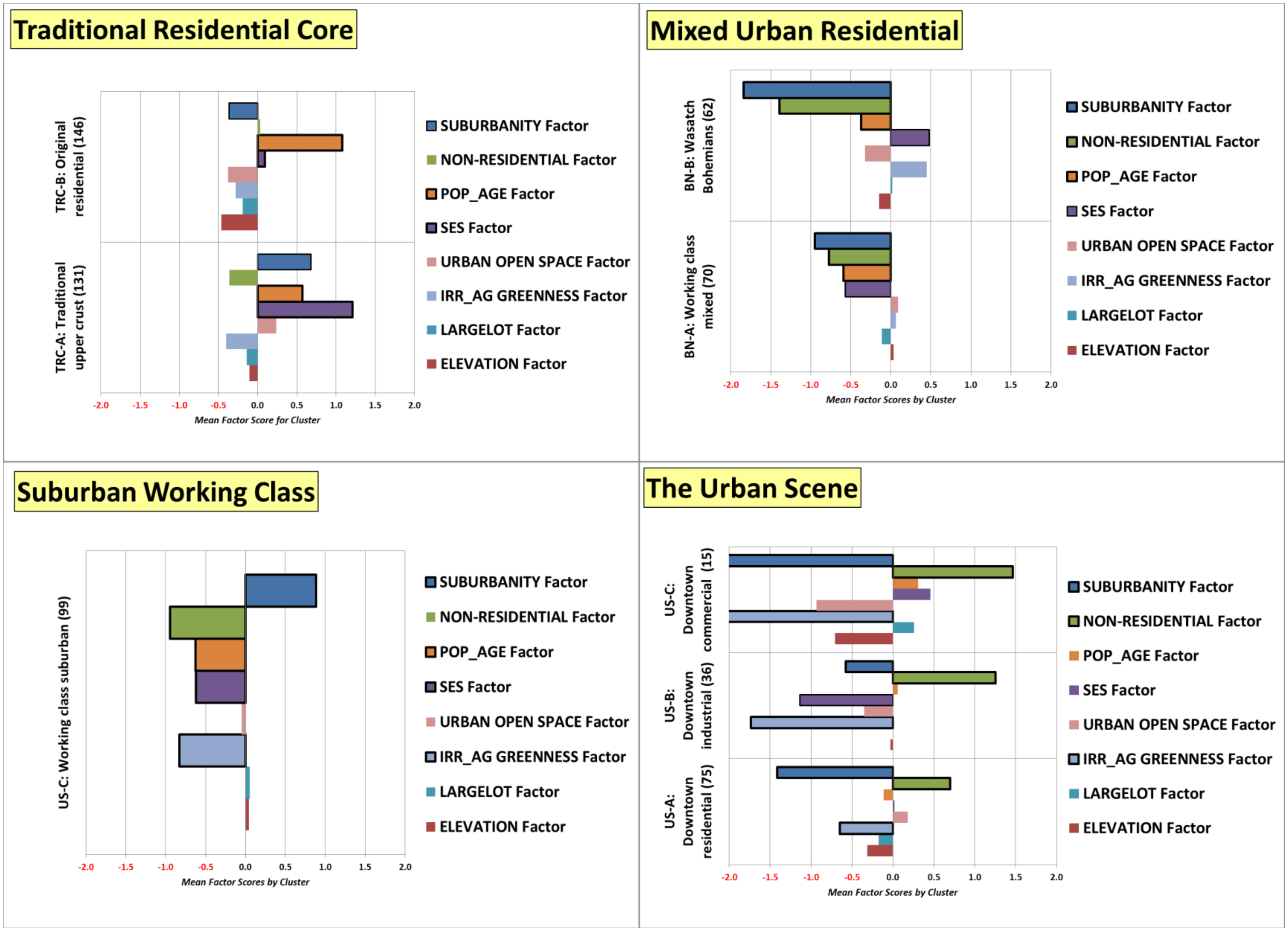

Figure 2b Mean factor scores by cluster groups and neighborhood types (continued).

Greenness and Urban Open Space

Combinations of two other factors reflect the types of land cover and amount of 'greenness' found within each census block group. Two major CGs are uniquely defined by their relatively high (Expanding City) or low (Urban Scene) scores on Irrigated Agriculture/Greenness (Factor 7). In the first instance, the cluster group includes CBGs located in transitioning areas at the urban fringe with significant amounts of remaining agricultural land use and exurban housing development. In the latter case, the remaining land cover has a much lower NDVI greenness score. Interestingly, among the two 'suburban' CGs, the Suburban Working Class cluster group is distinctive for having relatively low greenness.

A separate factor – Urban Parks and Open Space (Factor 8) – captures the percent of land area in a CBG that is in urban parks and open spaces. One major CG – Parkside Residential – is characterized primarily based on this factor. Both individual NTs in this group have scores on the urban open space factor that are 2 to 5 standard deviations above the average.

Socioeconomic Status and Age

Three major CGs are noted for having older than average populations and older housing stock: Moderate Middle, Traditional Residential, and Parkside Residential. By contrast, three CGs have notably younger housing stock and residents: New Suburban, Suburban Working Class, and Mixed Urban Residential.

Aside from the Suburban Working Class and Moderate Middle groups, the Socioeconomic Status (SES; Factor 4) scores did not define many major CGs, but rather SES characteristics serve to distinguish individual neighborhood types *within* several of the major cluster groups. For example, within each of the New Suburban and Traditional Residential CGs, a single NT (Suburban Elite and Traditional Upper Crust, respectively) present the two highest SES clusters in the WRMA. However, the other NTs in their CGs did not have notably high or low scores on the SES factor. Similarly, the four NTs with the lowest SES scores (Working Class Traditional, Working Class Mixed, Suburban Working Class, and Downtown Industrial) are each found in different cluster groups.

Elevation and Lot Size

Mean scores for the Microclimate (Factor 2) and Low Density Settlement (Factor 5) factors illustrate that two CGs (Expanding City and Urban Scene) tend to be found at lower elevations in valley floors with higher temperatures and lower rainfall, while one CG tends to be located at higher elevations with cooler and wetter climates (Moderate Middle). Neighborhoods in the Expanding City CG (particularly the Green Acres NT) are also defined by having larger than average lot sizes and lower settlement densities.

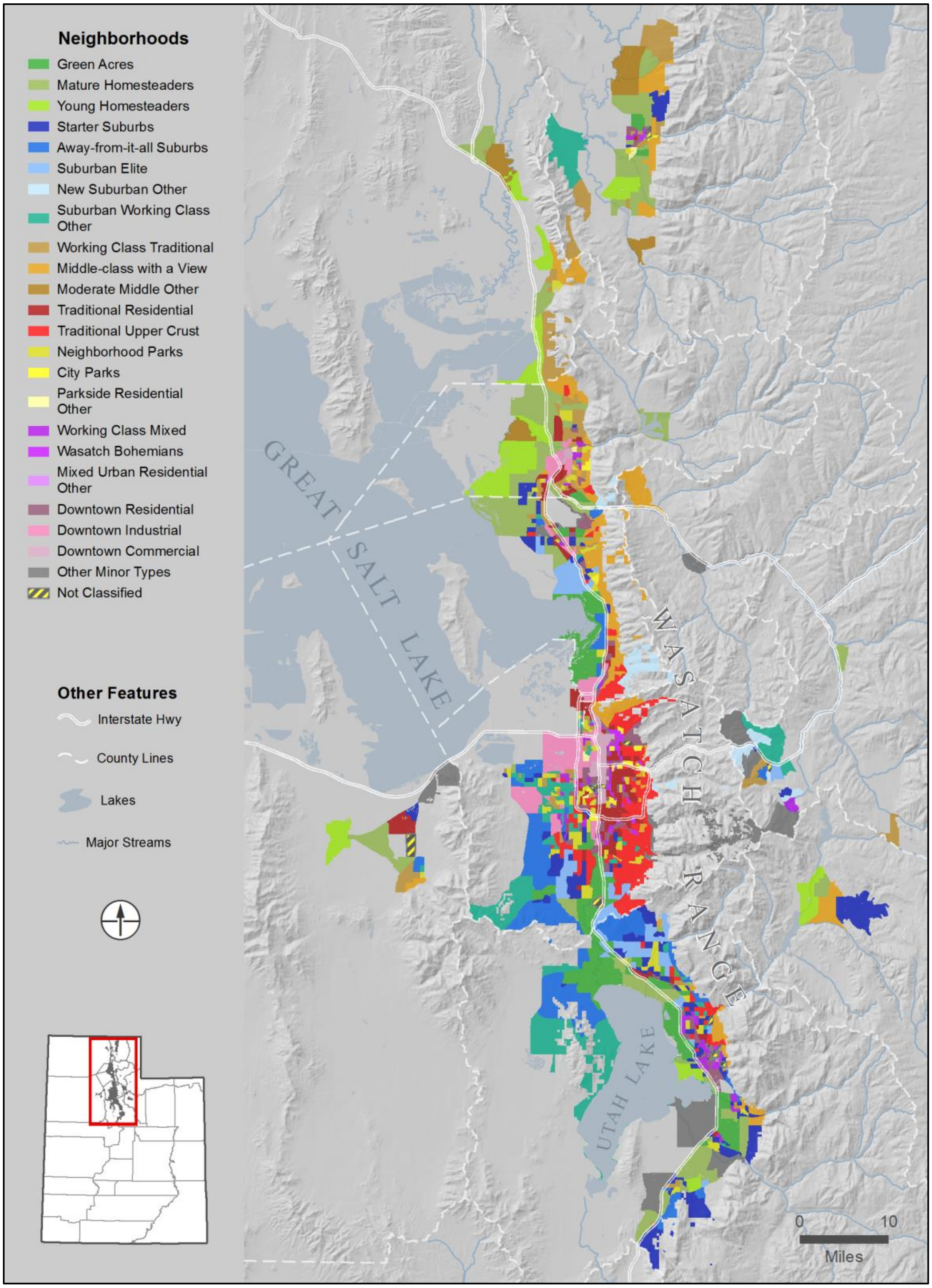

Figure 3 Distribution of Neighborhood Types (NTs) across WRMA. *Includes all census block groups with population density over 100 persons/sq.mile. See Supplemental Figure B for a more fine-grained illustration of the distribution of neighborhood types in a single county. See Supplemental Figures C and D for illustrations of the Cluster Group (CG) distributions.*

Uses of the Neighborhood Typology

The various combinations of distinctively high and low scores on the 8 factors used in our cluster analysis produced eight major cluster groups (CGs) that reflect unique combinations of urban characteristics on the core analytical factors. Moreover, within each major CG, individual neighborhood types represent distinctive combinations of unusually high or low scores on additional factors. As part of a larger study of urban water systems, the typology has been used to provide a conceptually and theoretically grounded basis for organizing our social and biophysical data collection and structuring our analysis of the impacts of natural, built, and social structures on urban water system processes and outcomes (iUTAH 2016).

For example, we have used the typology as an analytical tool for studying geographic patterns of water behaviors in urban water systems. Initially, parcel-scale water use data for a major metropolitan utility was used to assess the links between parcel attributes and indoor and outdoor water use rates. Indicators of neighborhood-level attributes from the typology were then included in a multi-level model. Controlling for parcel-scale attributes, results suggest that neighborhoods with high scores on the 'suburbanity' factor had markedly higher per parcel water use (Stoker et al. *In Review*).

A second example reflects results from an extensive survey of residential household water attitudes and behaviors conducted in summer 2014. Similar to Grove et al. (2015) and Zhou et al. (2008), we used the typology to stratify our sampling locations. Specifically, the survey was administered in 23 neighborhoods (CBGs) in 3 counties across the WRMA that were selected to include good exemplars of each of the major neighborhood types. Households were then randomly selected within each study neighborhood. A total of 2,343 households completed the survey, a response rate of over 62%, and respondents had characteristics that were consistent with attributes reported in recent census data (Jackson-Smith et al. *In Press*).

Selected summary statistics from the survey are broken out by Cluster Group type in Table 3. Bivariate tests demonstrate strong and statistically significant differences between CGs in how residents think about and make decisions regarding a range of landscaping and lawn watering practices. Residents in neighborhoods at the urban/rural fringe (Expanding City CGs) were least likely to have reduced indoor or outdoor water use in recent years, least concerned about water shortages, and least likely to agree that residential lawns use too much water.

Residents in the most urbanized neighborhood types (Mixed Urban Residential and Urban Scene CGs) were much less likely to have a lawn (at all) or to plant low water use plants on their properties, often had no responsibility for landscaping or irrigation decisions, but were more likely to say that residential lawns use too much water and that water conservation considerations are important in their water behaviors. Residents in the Traditional Residential Core and Parkside Residential neighborhoods were much more likely to have low water use plants, were more concerned about water shortages and deteriorating infrastructure, and reported some of the highest reductions in water use over the last 5 years. Finally, residents in New Suburban neighborhoods were least likely to say that water conservation was important in their landscaping and watering decisions, watered more days per week on average, but were among the most likely to use indoor water conservation practices.

Table 3 Attitudes, beliefs, and behaviors of adults living in different neighborhood types.

	a Expanding City	*b* New Suburban	*c* Suburban Working Class	*d* Moderate Middle	*E* Traditional Residential Core	*f* Parkside Residential	*g* Mixed Urban Residential	*h* Urban Scene	*Significance tests*	
				percent of respondents					*Chi-Sq.*	
Has lawn on property	92.0	94.5	**99.0**	93.4	94.4	100	**67.5**	75.9	*0.000*	
Has low-water use plants	32.9	31.4	**20.8**	34.0	46.4	**50.0**	27.9	30.1	*0.000*	
Household responsible for:										
Landscaping decisions	89.6	90.4	88.3	89.8	92.3	**97.0**	**53.8**	71.0	*0.000*	
Watering lawn	84.0	94.0	97.7	93.7	95.0	**98.1**	**52.4**	65.4	*0.000*	
Household decreased water use in last 5 years										
Indoors	**14.8**	17.2	22.5	**25.1**	24.6	22.0	21.7	19.6	*0.032*	
Outdoors	**12.5**	14.1	15.3	18.4	24.3	**28.7**	27.3	21.6	*0.002*	
				mean score of respondents					*ANOVA F-test*	*Pairwise Contrasts (LSD)*
Importance of minimizing water use in landscaping [i]	3.23	**3.18**	**3.82**	3.37	3.53	3.53	3.39	3.60	*0.000*	*a<c; a<e; a<f; a<h; b<c; b<e; b<f; b<h; c>d; c>g; d<h*
Mean days per week waters lawn in July	3.36	**4.05**	3.52	3.05	3.39	3.42	**2.90**	3.05	*0.000*	*a<b; a>d; a>g; b>c; b>d; b>e; b>f; b>g; b>h; c>d; c>g; c>h; d<e; d<f; e>g; f>g; f>h*
Index for use of indoor water saving practices [ii]	18.8	19.5	18.8	18.4	**19.7**	19.2	17.9	**17.5**	*0.000*	*a<b; a<e; a>g; a>h; b>d; b>g; b>h; c<e; c>g; c>h; d<e; d<f; d>h; e>g; e>h*
Concern about issues [i]										
Water shortages	**3.63**	3.68	3.96	3.64	4.03	**4.14**	3.68	3.85	*0.000*	*a<c; a<e; a<f; a<h; b<c; b<e; b<f; b<h; c>d; c>g; d<e; d<f; d<h; e>g; f>g; f>h*
High cost of water	3.83	4.20	**4.35**	3.84	3.89	4.14	**3.73**	3.95	*0.000*	*a<b; a<c; a<f; b>d; b>e; b>g; b>h; c>d; c>e; c>g; c>h; d<f; f>g; g<h*
Agrees that residential lawns use too much water [i]	**3.41**	3.68	3.56	3.61	**4.03**	3.93	4.00	3.98	*0.000*	*a<b; a<d; a<e; a<f; a<g; a<h; b<e; b<f; b<g; b<h; c<e; c<f; c<g; c<h; d<e; d<f; d<g; d<h*

NOTES: i = scale from 1 to 5; ii = scale from 1 to 25; highest and lowest values on each row are bolded.

DISCUSSION AND CONCLUSIONS

Studies of urban ecological systems require a sophisticated understanding of the complex arrangements of social, built, and biophysical components that comprise the urban landscape (Pickett and Grove 2009; Grove et al. 2015). A large literature has identified a number of characteristics of urban areas that are linked to water demand, water quality, and ecohydrology outcomes. Our work demonstrates that publically available data for 47 key variables at the neighborhood scale (operationalized as the census block group) can be used to identify a set of underlying dimensions (or statistical 'factors') that make urban neighborhoods distinctive in a particular region. Moreover, indicators for these dimensions can be used to create a typology of neighborhoods where each type (or 'cluster group') has distinguishing characteristics that are expected to be linked to a range of urban water system dynamics. We have demonstrated that neighborhood types are systematically linked to variation in attitudes towards water conservation and self-reported water use behaviors in this region. Ongoing research by members of our larger research team is exploring whether the hypothesized relationships between the typology classes and other water system outcomes (water quality, water budgets, and urban ecohydrology) are borne out in the field.

Our research is methodologically similar to other research that developed urban neighborhood typologies (Chow 1998; Shay and Khattak 2007), but is the first to develop a typology that fully integrates spatially explicit measures of *physical, built*, and *social* structures which have been linked to urban water system dynamics. The typology is built on socially-defined small area boundaries (census block groups) that more closely capture important household, neighborhood, and city governance system processes than more biophysically-defined units of analysis (e.g., subwatersheds derived from digital elevation maps). Our exclusive use of publicly available data sources overcomes some of the constraints associated with previous work that relied on commercially available demographic segmentation data (Grove et al. 2006a).

While data presented above primarily focuses on links between urban neighborhood types and water use, our urban typology provides an empirically grounded basis for designing field research projects to explore linkages between urban forms and a range of hydrologic outcomes and ecosystem services that are driven by flows and fluxes of water. We are exploring several key questions in our larger ongoing interdisciplinary research, including: How does urban form affect water use patterns and how can we design growth policies and plans to encourage more neighborhoods that promote long-term water sustainability? In what ways do patterns of infiltration, evapotranspiration, and stormwater runoff differ between neighborhoods? What aspects of urban neighborhoods are associated with various water quality outcomes and how might urban growth management tools be used to mitigate future negative impacts? How do neighborhood characteristics influence urban ecohydrology (particularly vegetation types, density, and biodiversity) and how can this knowledge be better incorporated into integrated urban water system modeling? Addressing these questions requires a systematic and theoretically grounded approach to classifying the urban landscape, and our urban neighborhood typology provides a basis for making these distinctions.

All of the variables used in our analysis were chosen because they can be easily obtained across the U.S., making our methods generalizable to other urban areas. However, since the specific cluster groups and neighborhood types were derived through an inductive statistical process using data from a particular region, we would anticipate that other metropolitan regions might identify somewhat different configurations of neighborhood types that reflect the local distribution of the underlying factors in their region. Additionally, the specific links between neighborhood characteristics and water use patterns presented above may well be different in other regions with different climate and built water system characteristics. Extending the spatial footprint of such a typology to include multiple metropolitan regions would reveal how commonalities and differences across neighborhood types affect urban water systems and help advance interdisciplinary urban water science.

There are a number of limitations of our approach that should be acknowledged. First, our methodology is dependent on a particular operationalization of the idea of ‘neighborhood’ (census block groups), and our results should only be generalized to this scale of analysis (Wong 2009). We also recognize that the statistical methods we utilized may require technical expertise that is not common among some non-academic organizations (public utilities, urban planners, etc.), which might limit the widespread use of our approach to classifying urban landscapes. Finally, there are a number of variables that would have been theoretically interesting to include, but were not readily available across our study area. Examples include soil maps to capture variation in the permeability and infiltration capacity of soils; the presence or absence of sewer service lines (versus septic tanks) and measures of the presence of different levels of stormwater management infrastructure. Future efforts to replicate versions of the typology in other regions are encouraged to take advantage of locally available datasets that capture these additional attributes.

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