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JUST OPEN A WINDOW: UNDERSTANDING THE VULNERABILITY TO SUMMER HEAT OF A MOUNTAIN COMMUNITY IN THE WESTERN UNITED STATES, MISSOULA, MT

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BY

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Just open a window: Understanding the vulnerability to summer heat of a mountain community in the western United States, Missoula, MT

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How do we conceptualize vulnerability or resiliency to a natural hazard when it has not historically been understood as such? This study focuses on Missoula, located in mountains of western Montana, which has steadily grown by 1-2% per year to almost 75,000 residents. The formerly temperate quality of its winters and summers has also been changing. Projections from the 2017 Montana Climate Assessment estimate the state will experience a 2-5°F increase in mean annual air temperature over the next two decades, prompting city and county officials to plan for scenarios not formerly in their consideration. Of further concern is the increasing frequency of extensive summer wildfires and accompanying poor air quality that prevents the low cost venting of homes during cooler evenings. This study was facilitated by the American Geophysical Union's Thriving Earth Exchange (TEX) collaboration between local (City of Missoula, Climate Smart Missoula), state (University of Montana), and national (TEX, University of Notre Dame) stakeholders seeking to create a climate change plan.

Areal interpolation from U.S. Census American Community Survey block-group data to the block level, and dasymetric mapping were utilized to account for the unpopulated public lands that occupy substantial portions of many blocks. Socioeconomic variable layers (age, income, education, employment, living alone, multi-unit housing, mobile housing, insurance status, and disability) were combined in a Multi-Criteria Analysis to map sensitivity and exposure variables of land surface temperature and land-cover data to predict the populations most vulnerable to heat (and smoke) risks. The resulting maps will be utilized by Missoula city and county planners to allocate resources for mitigation, such as recommendations for the selection of building materials in new construction, installation of cooling shelters, and enhancement of urban forest. This study was designed to develop a methodology that could be readily replicated by other small communities to implement and update as needed.

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Introduction

Known as the Garden City for its relatively clement weather, the population of Missoula, Montana, was 66,788 in 2010 and has been increasing by 1-2% per year (U.S. Census Bureau, 2010). Its temperate climate has been warming, with projections from the Montana Climate Assessment (Whitlock et al. 2017) estimating the state will experience a 2-5°F increase in mean annual air temperature over the next two decades, prompting city and county officials to plan for scenarios not formerly in their consideration.

Human vulnerability has been widely described in hazards literature across a variety of fields, from local studies (Armas 2013, Weis et al. 2016) to the U.S. Centers for Disease Control and Prevention (CDC) online platform designed to assess vulnerability at the census-tract level. Data-driven indices have been created to aid municipalities trying to anticipate and mitigate hazardous impacts to their community (Birkmann 2007). However, there has been no uniform protocol in the construct of a vulnerability index. Vulnerability may be defined quite differently depending upon the associated problem, and include socioeconomic, health, environmental, adaptation variables, or some combination. It is therefore incumbent on the researcher to both explain the concept and determine the variables to include.

There have been few studies examining vulnerability to heat stress in cities of similar physical and urban geography to Missoula. Local governmental and non-governmental organizations are incorporating climatic change in their growth and development plans, and requested assistance in helping to map the heat island and identify those most vulnerable to increasing heat stress. The research objectives are:

1) Define vulnerability for this study;

2) Determine and map the socioeconomic variables most representative of sensitivity to heat and smoke in Missoula City and County at the census-block level;
3) Utilize sensitivity and exposure data in a Multiple Criteria Analysis (MCA) to map overall vulnerability and provide context to inform future planning by city government and health officials;
4) Document the methodology such that stakeholders can update the analysis as needed and so that communities of similar size can adapt it for their own planning goals.

Background

Impetus for this study began with local organization Climate Smart Missoula, in collaboration with the City of Missoula Climate Office, University of Montana, and national partners the American Geophysical Union's Thriving Earth Exchange and University of Notre Dame. The initial working group was formed to examine the Urban Heat Island (UHI) effect during increasingly hotter, drier summers.

Urban Heat Islands and Human Health

UHI was conceptualized in the 19th century as applying to major cities, but is now considered an environmental hazard affecting many populated areas (Gartland 2008). A UHI can be 2-6°F (1.1-3.3°C) warmer than outlying rural landscapes during the day and as much as 22°F (12°C) warmer at night, the result of solar energy retained by dark surfaces used in paving, buildings, and roofing, impermeable materials which limit water infiltration and vegetation (US EPA 2016). Residential zones typically expand with population growth, and Missoula's built environment is spreading into the surrounding rural county.

Human health can be significantly impacted by increased temperatures. The National Oceanic and Atmospheric Association's National Weather Service lists heat as the largest cause of weather-related U.S. fatalities over the last 30 years (NOAA 2017). Past research has shown that persons disproportionately affected are small children, the elderly, those with disabilities, and those living alone (Nayak et al. 2009), in multi-unit buildings or mobile homes (Aminipouri et al. 2016). These social conditions may coincide with economic factors of income, employment, educational attainment, and availability of health insurance to increase sensitivity to heat (Reid et al. 2009).

Wildfire Smoke and Human Health

The smoke resulting from summer wildfires is also a health hazard in Missoula. Decades of fire suppression management combined with anthropogenic climate change have resulted in unprecedented fuel aridity, imposing "an increasingly dominant and detectable effect on western U.S. forest fire area" (Abatzoglou and Williams 2016). Where there's fire, there's smoke, and subsequent air quality deterioration. Particulate matter standards established by the U.S. Environmental Protection Agency regulate fine inhalable particles smaller than 2.5 micrometers in diameter ($PM_{2.5}$; EPA website accessed 2018) as a primary pollutant. Levels of $PM_{2.5}$ for annual exposure should not exceed 12 $\mu g/m^3$, or 35 $\mu g/m^3$ in a 24-hour period (EPA 2012). McClure and Jaffe (2018) found a striking increase in the number and concentrations of $PM_{2.5}$ and total carbon in most polluted days in the western US between 1988 and 2016. Wildfire smoke pollution is an issue for anyone attempting to work or recreate outside, but it is particularly detrimental to children, seniors, and those living in poverty (Rappold et al. 2017). Unsurprisingly, heat and smoke affect similar populations: those with immature or compromised adaptation to physical stress, and those at income levels prohibitive to cooling or filtration systems (Farbotko and Waitt 2011).

Defining Vulnerability

The concept of vulnerability is complex and evolving, varyingly labeled sensitivity, deprivation, insecurity, or a component of risk. The Intergovernmental Panel on Climate Change (IPCC 2014) defines vulnerability as “a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity.” Distinguishing between sensitivity and adaptive capacity is challenging. The United States Agency for International Development commissioned a review of vulnerability assessment (USAID 2014) that found the same variable could indicate high sensitivity yet be a measure of low adaptive capacity. These authors caution that collapsing the two makes it later impossible to address them separately in a policy context, which is one of the objectives of this study. Therefore, vulnerability is defined here as:

$$\text{Vulnerability} = \text{Sensitivity} + \text{Exposure}.$$

This study will draw upon disparate sources of socioeconomic, satellite-derived, and particulate data, to map where vulnerable groups reside in Missoula.

Study Area

Missoula County resembles the rest of Montana in that the places where people reside are limited by topography and extensive public lands (Figure 1). The U.S. Department of Commerce (1994) describes U.S. Census units in western states as large, sparsely populated and irregular, due to settlement patterns that relied primarily on land features. Missoula County has 76 block groups containing 5,863 blocks (U.S. Census 2010).

The City of Missoula is a small metropolitan center with an estimated (U.S. Census 2016) population of 72,000 within a 29 mi^2 (75 km^2) area, within a county that is largely rural (116,000 in 2,600 mi^2 (6734 km^2; Figure 2). While urban services are most accessible within Missoula's city limits, planning efforts include newly incorporated areas (such as the airport) and those expected to be incorporated in the near future. To provide greater spatial detail of the residential population, a rectangular area encompassing land adjacent to the city was used for mapping when the entire county was not shown (Figure 2).

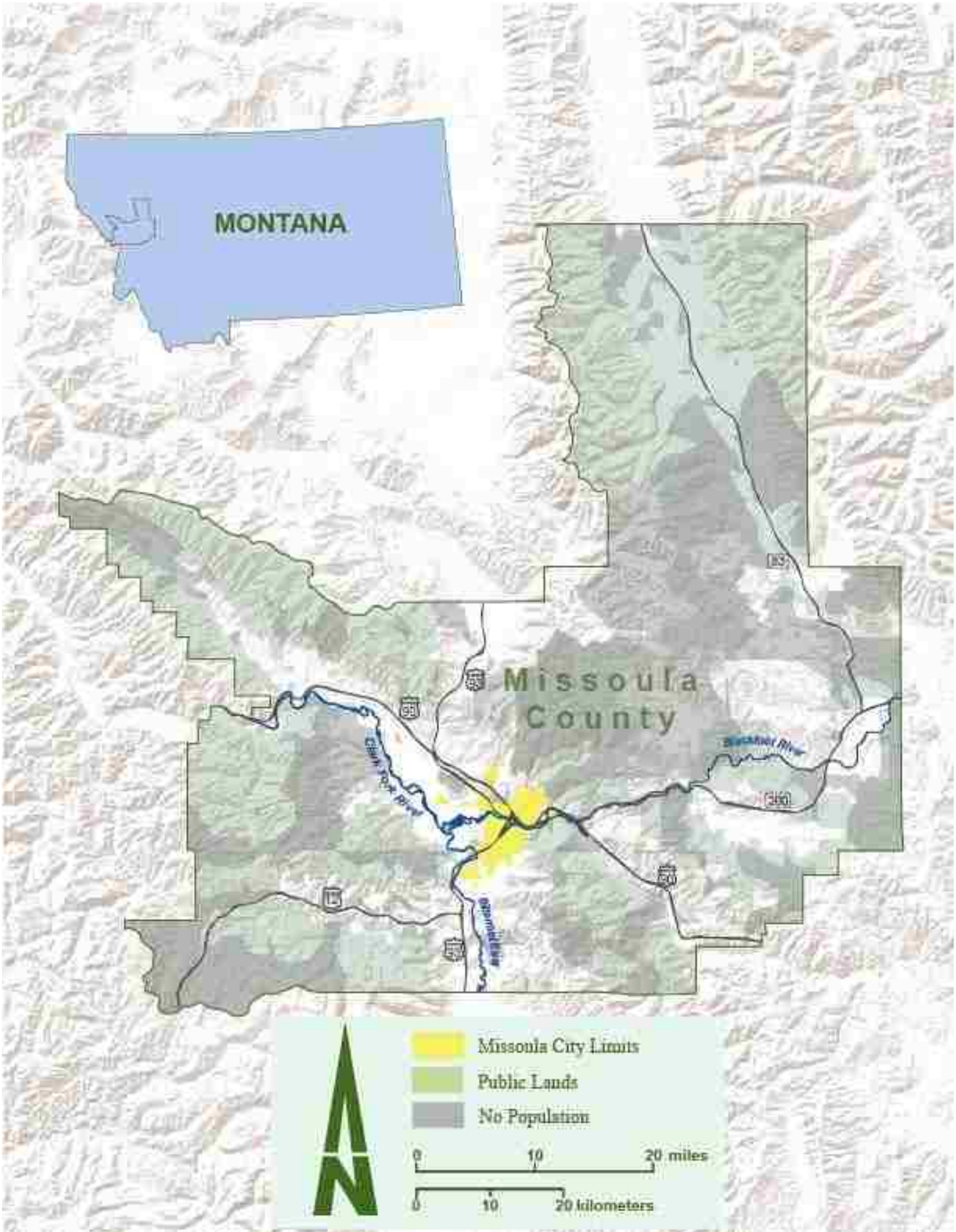

Figure 1: Map showing the location of Missoula County within the state of Montana, displaying 2018 city limits, unpopulated and public lands.

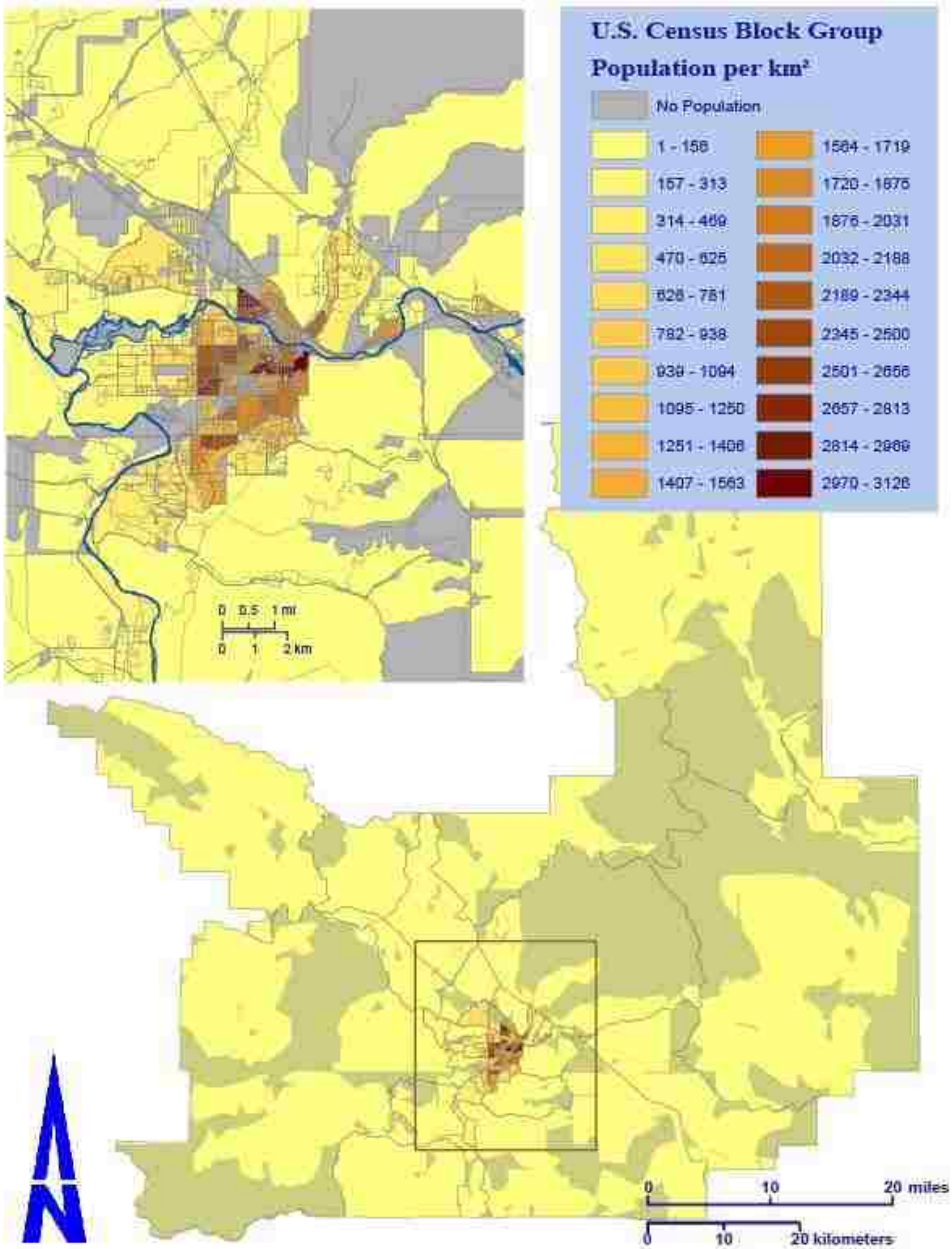

Figure 2: Missoula County population density within U.S. Census Block Groups and study area inset.

The Montana Climate Assessment (Whitlock et al. 2017) shows average temperature in the western region of the state increased by 0.4°F/decade, 1950-2015. Maximum July temperatures in Missoula have increased 0.6°F/decade over that same period (www.missoulaclimate.org accessed October 2018). Hotter summers with no increase in precipitation have been observed since 1950, increasing wildfire potential, and this trend is forecast to continue in coming decades (Whitlock et al. 2017).

The Montana Department of Environmental Quality's air monitoring station in Missoula's Boyd Park has measured air quality hourly since 1981. During fire season (mid-summer through fall) these readings can far surpass the exposure standards yet are categorized as "exceptional events" which are not included in the annual average for regulatory purposes (Montana DEQ 2001). The American Lung Association (www.lung.org accessed October 2018) ranks Missoula 12th out of 201 U.S. metropolitan areas in terms of 24-hour particle pollution, a failing rating.

Missoula lies 3,209 ft (978 m) above sea level, which has typically allowed residents to manage summer heat by opening their homes at night to let in cooler air that settles on the valley floor. However, mountain valleys tend to trap smoke and reduce vertical mixing, exacerbating and prolonging pollution events caused by wildfires in surrounding forests. This community is especially challenged by these two natural hazards acting together.

Data and Methods

The Community Health Assessment (2017) published by the Missoula City-County Health Department addresses climate change as an indicator of health, and includes vulnerability maps using data from the CDC's Behavioral Risk Factor Surveillance System (BRFSS). However, the BRFSS's statewide sampling and lack of geographic coordinates at the block group or block level, limit its application. Additionally, detailed spatial data on hospital admissions or emergency response due to heat-related illnesses could not be obtained at this time due to the confidential and proprietary nature of the data. This led to the use of socio-economic data, rather than health-outcomes to estimate vulnerability.

Socioeconomic Sensitivity Variables

Detailed socioeconomic data collected as part of the U.S. Census American Community Survey (ACS) are only available at the block-group level. The ACS can cover one-, three-, or five-year periods during which demographic data are collected every month to represent the attributes of populations and households. The most recent dataset available, 2012-2016, was selected since the five-year sample size is the largest available for small populations, such as Missoula (U.S. Census Bureau, 2009). Variables were chosen based upon social vulnerability research best practices (Cutter et al. 2003; EPA and CDC 2016) and focused on heat and smoke health risk studies (Table 1: Ho et al. 2015; Nayak et al. 2017; Rappold et al. 2017). Data for each variable were downloaded from the American FactFinder portal (accessed February 2018) at the block (age and population) and block group scale (other variables) for Missoula County (Table 2). Corresponding TIGER/Line shapefiles for Missoula County were also downloaded.

Table 1: Comparison of socioeconomic variables from related studies (Ho et al. 2015; Nayak et al. 2017; Rappold et al. 2017) and those selected for this study.

Data Variable	Vancouver 2015 (Heat)	New York State 2017 (Heat)	North Carolina 2017 (Smoke)	Missoula 2018 (Heat and Smoke)
Age (infant/toddler)	Yes – under 5	No	No	Yes – under 5
Age (senior)	Yes – 65 and over	Yes – 65 and over	Yes – 65 and over	Yes – 65 and over
Income	Yes – Less than $20,000 CAD	Yes – Below Poverty	Yes – Median household	Yes – Less than $25,000 USD
Education	Yes – No diploma or degree	No	Yes – H.S. education and above	Yes – No diploma or degree over 25
Employment	Yes – Unemployment rate	Yes – Unemployed 18-64	Yes – Unemployment rate	Yes – Unemployed over 16
Living Alone	Yes	Yes – Individual & over 65	No	Yes
Living in Older Home	Yes – Built before 1970	Yes – Built before 1980	No	No
Living in Multi-Unit	Yes	Yes – Density per sq mile	No	Yes – Over 10 units
Living in Mobile/RV	Yes	No	No	Yes
Disability	No	Yes	No	Yes
Other Socioeconomic:	No	Hispanic, Black, foreign born, does not speak English well	No	No
Exposure:	LST	2011 NLCD	$PM_{2.5}$	LST, 2011 NLCD
Health:	No	No	Asthma, COPD, Diabetes, Hypertension, Obesity	No
Data Scale:	2006 Canadian dissemination area unit (400-700 persons per)	2010 Census tract	2010 Census Counties	Census block groups estimated to blocks
Method:	MCA	PCA	PCA	MCA

Abbreviations: HS = high school; LST = Land surface temperature; NLCD = U.S. National Land Cover Dataset; $PM_{2.5}$ = 2.5 µm particulate; COPD = Chronic Obstructive Pulmonary Disease; MCA = Multi-Criteria Analysis; PCA = Principal Components Analysis.

Table 2: List of each sensitivity and exposure variable description, scale, and source. U.S. Census Bureau American Community Survey (ACS) five-year 2012-2016 data were the most recent available and all were accessed in February 2018*.

Sensitivity Variable	**Scale and Description**	**Source**
Population 65 and Over Population 5 and Under Population Over 16 Unemployed Population Over 25 with No H.S. Diploma Population without Health Insurance Household with Resident Living Alone Household with Resident with a Disability Household with Income < $25,000/year Household in Mobile Home/RV Household in Multi-Unit Housing	2010 Census block 2010 Census block 2012–16 ACS block group 2012–16 ACS block group 2012–16 ACS block group 2012–16 ACS block group 2012–16 ACS block group 2012–16 ACS block group 2012–16 ACS block group 2012–16 ACS block group	See above
Exposure Variable	**Scale and Description**	**Source**
95% Maximum Land Surface Temperature	30 m, USGS Landsat 8 April 11, 2013 – December 31, 2016	Silverman 2017
2011 Percent Impervious Surface	30 m, 2011 National Land Cover Database (NLCD)	Homer et al. 2015
2011 Percent Tree Canopy	30 m, 2011 National Land Cover Database (NLCD)	Xian et al. 2011

Areal Interpolation and Dasymetric Mapping

Areal interpolation is an established method in which the characteristics of one geographic zonation are transferred to the population of a different zonation (Goodchild et al. 1992). In this study, ACS block group socioeconomic variables were estimated proportionally to either population or household counts within individual blocks. Although the ACS data is more recent, it was assumed that population within the 2010 census blocks remained proportional to that within the block groups. Data were mapped as population or household density rather than raw counts. A detailed work flow of the areal interpolation of the ACS data is in Appendix A.

Dasymetric mapping (EPA 2015) is a method to more accurately represent the spatial location of population. In this case, a public lands dataset was downloaded from the Montana State Library (MSDI accessed July 2018) and populated blocks were clipped to exclude areas (Figure 1): city, county, and state parks, state trust lands, designated open space, Montana Fish, Wildlife, and Parks (FWP) holdings, Bureau of Land Management (BLM) land, and U.S. Forest Service (USFS) property. Montana University System (MUS) lands range from homes within city blocks adjacent to campus to University of Montana playing fields and much of Mount Sentinel, and thus were not entirely excluded. The University of Montana campus has several residence halls making it the most populous block in the county. However, the Census only lists two households in that block as group housing is not counted as household. After excluding these large areas, the density of each socioeconomic variable was mapped (Appendix C) as per population or per household according to how the variable was defined (Table 2).

Physical Exposure Variables

As shown in Table 1, similar studies have used health variables, Land Surface Temperature (LST), or one or more components of land cover to estimate exposure. LST was mapped by one of the authors of the 2017 Montana Climate Assessment for this study (Silverman 2017). Satellite data at ~30 m resolution for Missoula County was acquired from the U.S. Geological Survey (USGS) Landsat 8 satellite archive (accessed 2017) for the period April 11, 2013 - December 31, 2016 to temporally match the ACS data. LST was calculated following Jimenez-Munoz et al. (2009) using the Google Earth Engine platform (Gorelick et al. 2017), with the mean calculated from the warmest 95th percentile to represent the distribution of extreme heat exposure. Surface temperature does not represent actual temperature experienced by an individual. As noted by Ho et al. in their 2015 and 2017 studies, air temperature and relative humidity influence apparent temperature, but it is difficult to quantify and map.

The presence or absence of some land-cover types provide another method to quantify exposure to heat (Manangan et al. 2014). The 2011 National Land Cover Database (NLCD) for the conterminous U.S. is the most current available (MRLC accessed 2018), and categorize sixteen land-cover classes at 30 m resolution. Studies utilizing NLCD (Hondula et al. 2015; Nayak et al. 2017) do not order those classes in terms of their heat-mitigating capacity, but sometimes follow the method of Reid et al. (2009) by aggregating land cover to determine a percentage of 'green space' by an area such as a census block group. NLCD data also includes layers of percentage of impervious surface (Homer et al. 2015) and tree canopy (Xian et al. 2011) at 30 m resolution. Impervious surfaces are a primary driver of the Urban Heat Island effect due to their heat-retaining properties and lack of evapotranspiration (Jesdale et al. 2013). Trees naturally mitigate heat and reduce air pollution (Nowak et al. 2013), with dense shade capable of significantly reducing summer energy consumption attributable to air conditioning (Pandit and Laband 2010). These two layers at 30 m were most easily comparable to the census-block scale of the socio-economic variables. Maps of LST, and percentage of impervious surface and canopy are in Appendix C.

The Boyd Park air monitoring station in south central Missoula provides hourly $PM_{2.5}$ readings. These were obtained from the Montana DEQ Air Quality Bureau (received 2018) for August 1 – September 30 of each year, 2012-2016. August and September are months with average high temperatures over 85°F and low precipitation, when hazard from wildfire smoke occurs. Particulate data for the wildfire season were requested to calculate the number of days when acceptable $PM_{2.5}$ thresholds were surpassed at the Boyd Park station. In September 2012, twelve days exceeded the EPA's $35 \mu g/m^3$ standard for a 24-hr exposure, and in August 2015 eleven days, two of which were over three times the standard (Figure 3).

Spatial estimation of particulate concentrations from one observation location was beyond the scope of this study. Archival data exists for wildfire incidents surrounding the study area, though satellite imagery of smoke distribution is unavailable at a spatial and temporal resolution comparable to the ACS data (Gaither et al. 2015). Inclusion of a spatial layer of exposure to smoke as even across the county was rejected in favor of simply stating that the risk from heat is exacerbated by smoke, that the sensitivity factors selected also reflect smoke susceptibility, and that the vulnerabilities can be interpreted as applying to both heat and smoke.

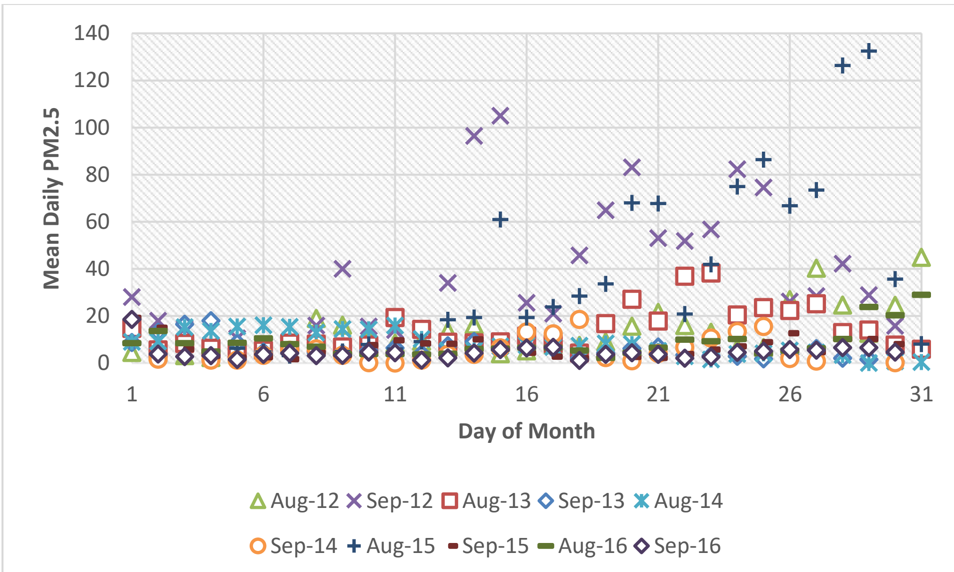

Figure 3: Daily mean particulate concentration ($PM_{2.5}$) at Missoula's Boyd Park monitoring station, August and September 2012-2016.

Multi-Criteria Analysis

The U.S. Agency for International Development (USAID 2013) recommended use of Multi-Criteria Analysis (MCA) in assessing adaptation to climate change, because it is a way to incorporate disparate sources of data at multiple scales for the use of a variety of stakeholders. Analysis is characterized by the ability to weight various criteria according to available expert knowledge. Transparency is essential in detailing variable selection and weighting during the creation of the MCA. Conversely, this method can be suitable in the *absence* of expert knowledge, when no single variable is assumed to hold greater significance than another and all are weighted equally. This approach has been widely used in vulnerability studies (e.g., UNEP 2003; Ho et al. 2015) and was utilized here because stakeholders did not have expert knowledge to distinguish any socioeconomic or exposure variable from another, health outcome data was unavailable at a scale comparable to census blocks, and the stakeholders wanted a method that was easily replicable and transparent. While the assumption of equal weighting is implicitly a decision that all factors are equally important, it is reasonable in the absence of evidence or expert knowledge to guide the weighting (USAID 2013; Woodruff et al. 2017). This study sought to examine the combined risk of heat and smoke. In separate publications, the EPA (2016 a, b) established that similar factors of age, socioeconomic status, and housing increase sensitivity to both, but no other study has assessed how each exposure contributes, which further reduced the availability of expert knowledge to determine weighting.

Principal components, factor, or cluster analysis were not utilized for the main analysis because these approaches can make the aggregation of data less clear for the audience it is designed to inform (Aubrecht and Özceylan, 2013). However, correlation analysis and PCA were utilized to quantify the relationships between the sensitivity and exposure variables.

ArcMap[1] was selected due to its widespread use, including by Missoula City and County stakeholders. Polygon layers of each sensitivity indicator (Table 2) were rasterized to match the ~30m exposure layers. Each sensitivity and exposure layer was reclassified into a uniform number of classes. Because of the population density of Missoula County, socioeconomic variables skewed toward low sensitivity except in the metropolitan area. While outliers can be removed to achieve a more normal distribution, exclusion of outliers in each layer (such as densely populated blocks of the University campus or very small blocks containing one

[1] ESRI ArcGIS Version 10.6.1, Redlands CA.

household/family) would remove key blocks that reflect the data distribution. Instead, a larger number of classes (20) was used to more accurately represent the distribution.

ArcMap's weighted overlay tool was utilized first on the reclassified sensitivity layers with equal weighting applied. Because the 10 variables were uniformly set at 20 classes, an evaluation scale of 1 to 20 intervals was selected, and each weighted at 10% to sum to 100%. The resulting layer displays areas of sensitivity from low to high. The exposure layer was created by a weighted overlay of LST, the NLCD impervious, and NLCD canopy layers each at 33% weighting. The final overlay weighted the combined sensitivity and exposure layers each at 50% weight.

Results and Discussion

Socioeconomic Sensitivity Variables

Individual maps of socioeconomic sensitivity variables are in Appendix C. Each was symbolized with twenty equal-interval classes, however, very small blocks are difficult to see (the highest density in the "population under 5" variable was a family of five living within a Census block of 0.00026 km^2). This reflects block configuration and while not optimal, could not be corrected without aggregating individual blocks. Generally, the maps displayed blocks consistent with the expectation of local residents on the TEX team. Blocks with high scores in the categories of over 65, low income, living alone, resident with a disability, and residence in multi-unit housing contain large assisted-living facilities for seniors. Two blocks with high density of low income, uninsured, and unemployed include apartment complexes considered the most affordable in the downtown area.

Principal Components Analysis (PCA) was performed on the sensitivity variables to determine the relationship between inputs. The highest correlations (Table 3) were between low income, living alone, and disability; the lowest correlations were between the age variables and others. Table 4 shows the percent of variance in the variables explained by each of the principal component's (PCs), as well as the loadings, or correlations between each PC and the input variables. The first component explained 66% of the variance within the socioeconomic sensitivity variables, and that PC had a correlation of 0.65 to 0.95 with each variable. The second component explained almost 10% of the variance and was most strongly correlated with age and unemployment.

Table 3: Correlation matrix for the 10 socioeconomic sensitivity variables described in Table 2.

	Live Alone	No Diploma	Disability	Low Income	Mobile	Multi-Unit	Over 65	Under 5	Un-employed	Un-insured
Live Alone	1	0.712	0.860	0.909	0.494	0.669	0.587	0.621	0.675	0.784
No Diploma	0.712	1	0.757	0.746	0.640	0.571	0.447	0.591	0.661	0.833
Disability	0.860	0.757	1	0.892	0.665	0.742	0.673	0.611	0.689	0.789
Low Income	0.909	0.746	0.892	1	0.511	0.827	0.569	0.547	0.645	0.779
Mobile	0.494	0.640	0.665	0.511	1	0.364	0.423	0.459	0.536	0.612
Multi-Unit	0.669	0.571	0.742	0.827	0.364	1	0.551	0.331	0.406	0.573
Over 65	0.587	0.447	0.673	0.569	0.423	0.551	1	0.285	0.366	0.442
Under 5	0.621	0.591	0.611	0.547	0.459	0.331	0.285	1	0.525	0.649
Un-employed	0.675	0.661	0.689	0.645	0.536	0.406	0.366	0.525	1	0.732
Un-insured	0.784	0.833	0.789	0.779	0.612	0.573	0.442	0.649	0.732	1

Table 4: The percent variance explained by each Principal Component (PC) and the loadings (correlations) between each PC and the socioeconomic sensitivity variables in Table 3.

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10
Variance Explained	66.57%	9.87%	6.50%	4.97%	4.34%	2.87%	2.09%	1.47%	0.86%	0.46%
Living Alone	0.909	-0.092	-0.188	0.084	0.111	-0.055	-0.288	-0.051	0.103	-0.101
No Diploma	0.862	0.190	0.026	-0.160	-0.130	0.364	0.045	-0.204	-0.003	-0.015
Disability	0.949	-0.114	0.056	0.035	-0.009	-0.117	-0.028	-0.024	-0.253	-0.047
Low Income	0.925	-0.209	-0.201	-0.087	-0.042	-0.080	-0.116	-0.052	0.004	0.171
Mobile	0.694	0.273	0.578	-0.113	-0.232	-0.188	-0.054	0.012	0.066	0.004
Multi-Unit	0.748	-0.497	-0.183	-0.172	-0.240	-0.098	0.231	0.044	0.068	-0.055
Over 65	0.648	-0.494	0.390	0.326	0.221	0.152	0.063	0.021	0.035	0.024
Under 5	0.689	0.423	-0.210	0.506	-0.155	-0.069	0.130	-0.014	0.0238	0.013
Un-employed	0.771	0.307	-0.026	-0.201	0.467	-0.135	0.175	-0.038	0.029	0.001
Un-insured	0.893	0.218	-0.079	-0.099	0.003	0.200	-0.047	0.309	-0.014	0.005

Sensitivity Analysis

MCA/weighted overlay of the 10 socioeconomic variables with equal weighting applied (10% each) results in an overall picture of heat sensitivity (Figure 4). Weighted overlay matches the number of classes in input layers with the number of intervals. This resulted in an overall additive range to 11, due to no block having values in the upper range in all layers. In this sensitivity overlay, the blocks containing assisted living and affordable apartment complexes are among those with the highest scores. High scores also occurred in a sawtooth-shaped area south of the Missoula City Cemetery near the railroad in the Westside neighborhood; these blocks contain a number of low-income housing options including mobile home parks.

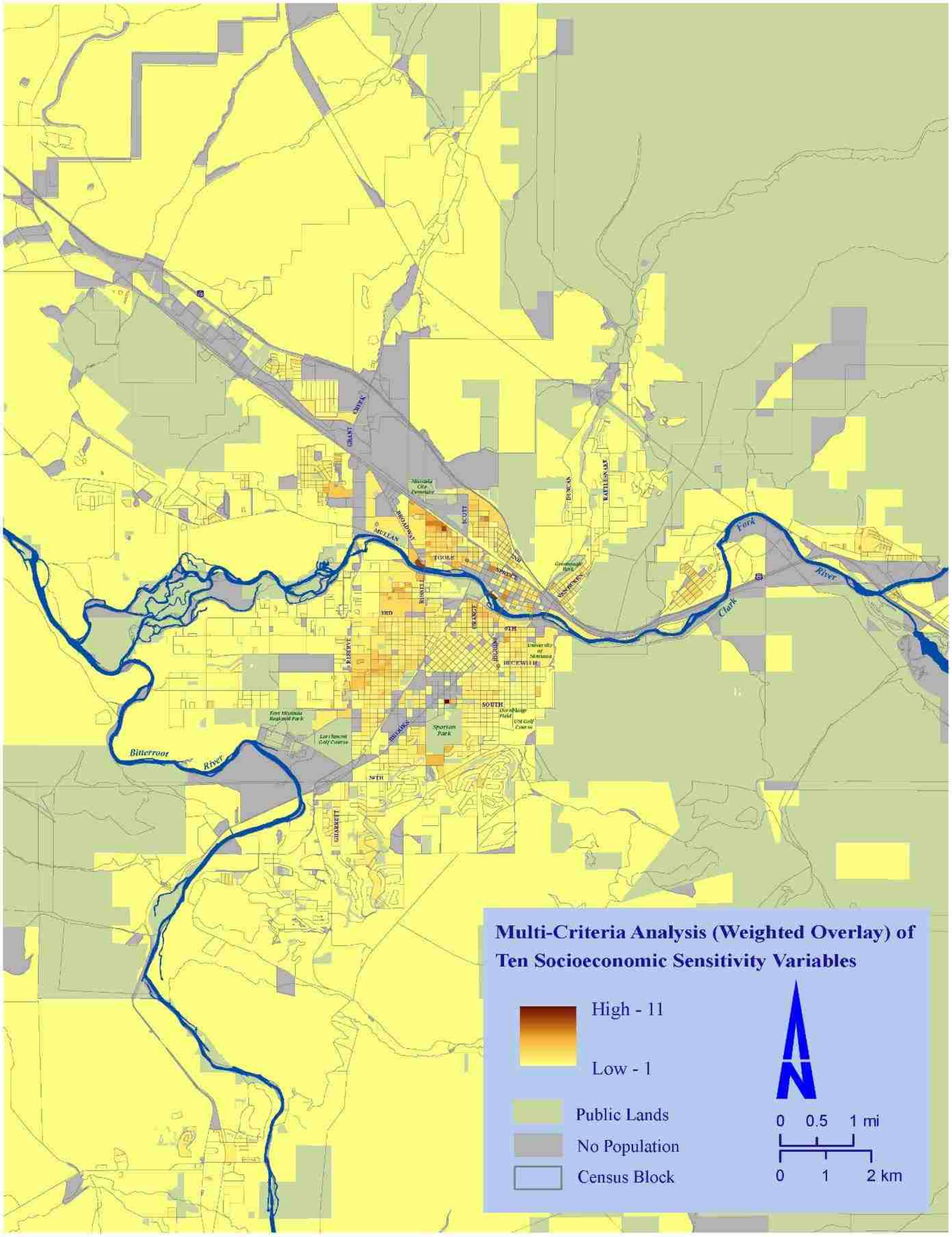

Figure 4: MCA weighted overlay of ten socioeconomic sensitivity variables (Table 2) in Missoula. Twenty was the maximum score possible if a pixel had the highest score in each variable.

Exposure Variables

There were three forms of exposure, all at ~30 m resolution: land surface temperature (LST), percentage of impervious surface, and percentage of tree canopy. Maps of these layers can be found in Appendix C. PCA was also performed on the exposure layers. The correlation matrix (Table 5) shows canopy and LST had an inverse correlation of -0.73. Impervious cover was not strongly correlated with either canopy or LST. The first PC accounted for 60% of the variance within the exposure variables (Table 6), and that PC had a correlation of 0.40 to 0.90 with each variable. The second component explained almost 30% of the variance and was strongly correlated (-0.83) with the impervious surface layer. The third (and last) component explained 9% of the variance and was negatively correlated (-0.37 and -0.32, respectively) to canopy and LST.

Table 5: Correlation matrix for the exposure variables described in Table 2.

	Canopy	**Impervious**	**LST**
Canopy	1	-0.178	-0.727
Impervious	-0.178	1	0.203
LST	-0.727	0.203	1

Table 6: The percent variance explained by each Principal Component (PC) and the loadings (correlations) between each PC and the exposure variables in Table 5.

	PC1	PC2	PC3
Variance Explained	60.45%	30.39%	9.17%
Canopy	0.905	0.196	-0.373
Impervious	0.409	-0.836	0.007
LST	-0.884	-0.223	-0.323

Exposure Analysis

The original purpose of this study was to assess Missoula's Urban Heat Island, which could be done with LST as the only exposure variable. Percentage of impervious surface and tree canopy were introduced to provide additional exposures following similar studies, and to determine if, when in combination with sensitivity, different patterns of vulnerability would be shown.

The 95th percentile LST for the period April 11, 2013 – December 31, 2016 (Silverman 2017) shows the warmest areas outside the city include south-facing slopes, highway corridors, and the Missoula County Airport. Within the city, highest temperatures correspond to areas known to have limited vegetation and extensive paving, such as between North Russell and Reserve Streets, between Mullan Road and West Broadway, and along Brooks Street (Highway 12) corridor. Cooler areas lie within heavily treed residential neighborhoods and city parks.

The 2011 NLCD layer for percentage of impervious surface (Homer et al. 2015) shows that the higher temperatures on the LST layer typically correspond to areas with most impervious surface and clearly maps the city's street grid. An assumption might be that areas without significant impervious surface would have a high amount of tree canopy, but that is not the case in the NLCD percentage of tree canopy (Xian et al. 2011) layer due to the arid environment of western Montana. The Missoula valley floor is largely without trees, except along rivers, in the Greenough Park and Pattee Canyon areas, and University of Montana neighborhood east of Higgins Avenue.

Smoke Exposure

While smoke exposure was not able to be depicted spatially for the period of time used for this study, 2012-2016, the increasing threat this poses to vulnerable populations should not be ignored. The EPA developed a Community Health Vulnerability Index (2017) for wildfire smoke exposure including several of the same socioeconomic indicators as that for heat. The index was considered for this study, but the interpolation of data from county scale to census block was not appropriate. It would be reasonable to assume an entire county or city has an exposure to smoke which, depending upon the year, could be weighted as large, or larger than, the other three exposure variables that could be spatially defined. As the resolution and availability of maps of the spatial modeling of wildfire smoke develop, this measure of exposure could be added to the MCA/weighted overlay.

Vulnerability Analysis

For this study, vulnerability was defined by sensitivity combined with exposure. Three weighted overlays were performed to compare the influence of the potential exposure variables in mapping vulnerability (Figures 5-7).

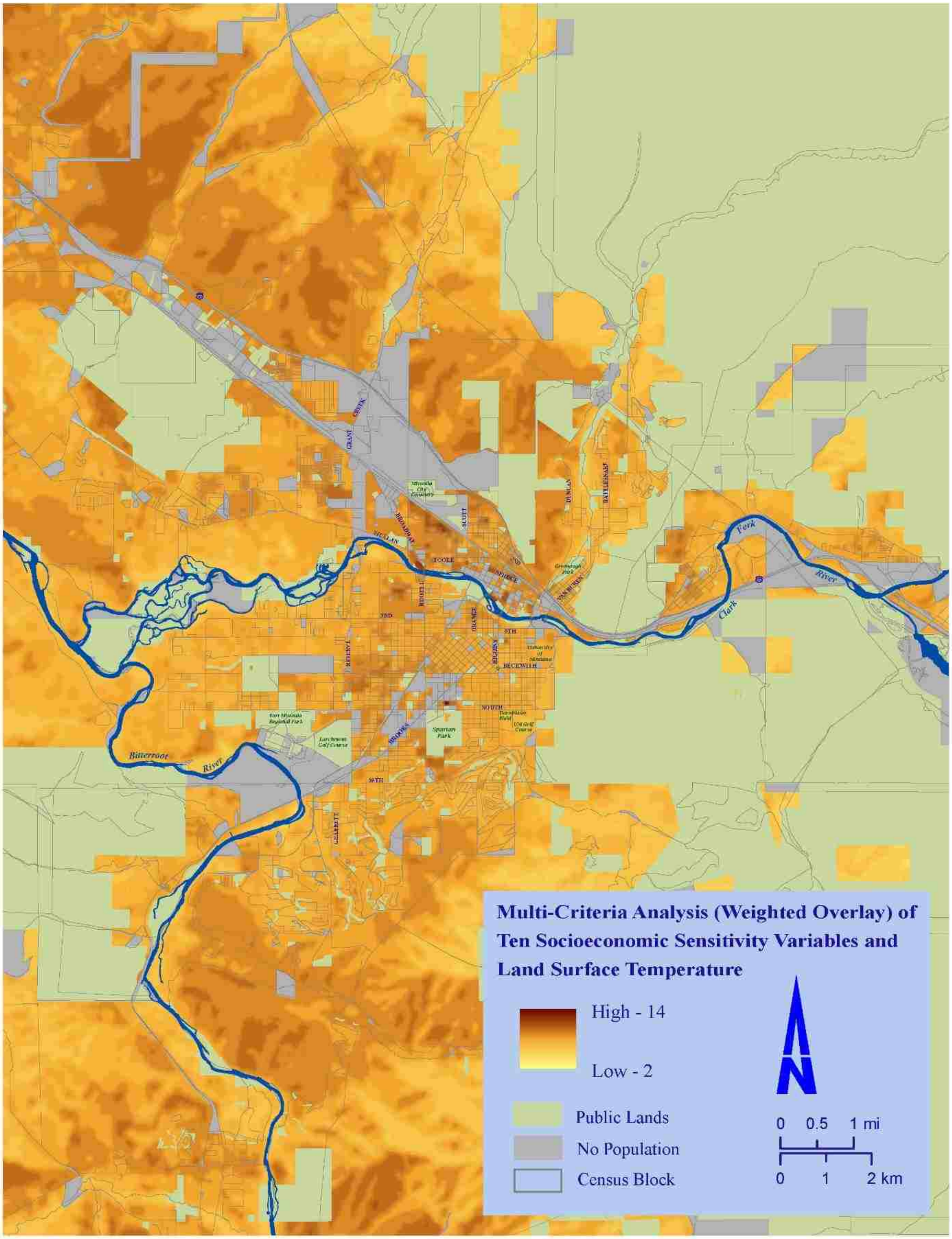

Figure 5: Weighted overlay of the sensitivity layer (Figure 4; 50%) with LST exposure layer (50%).

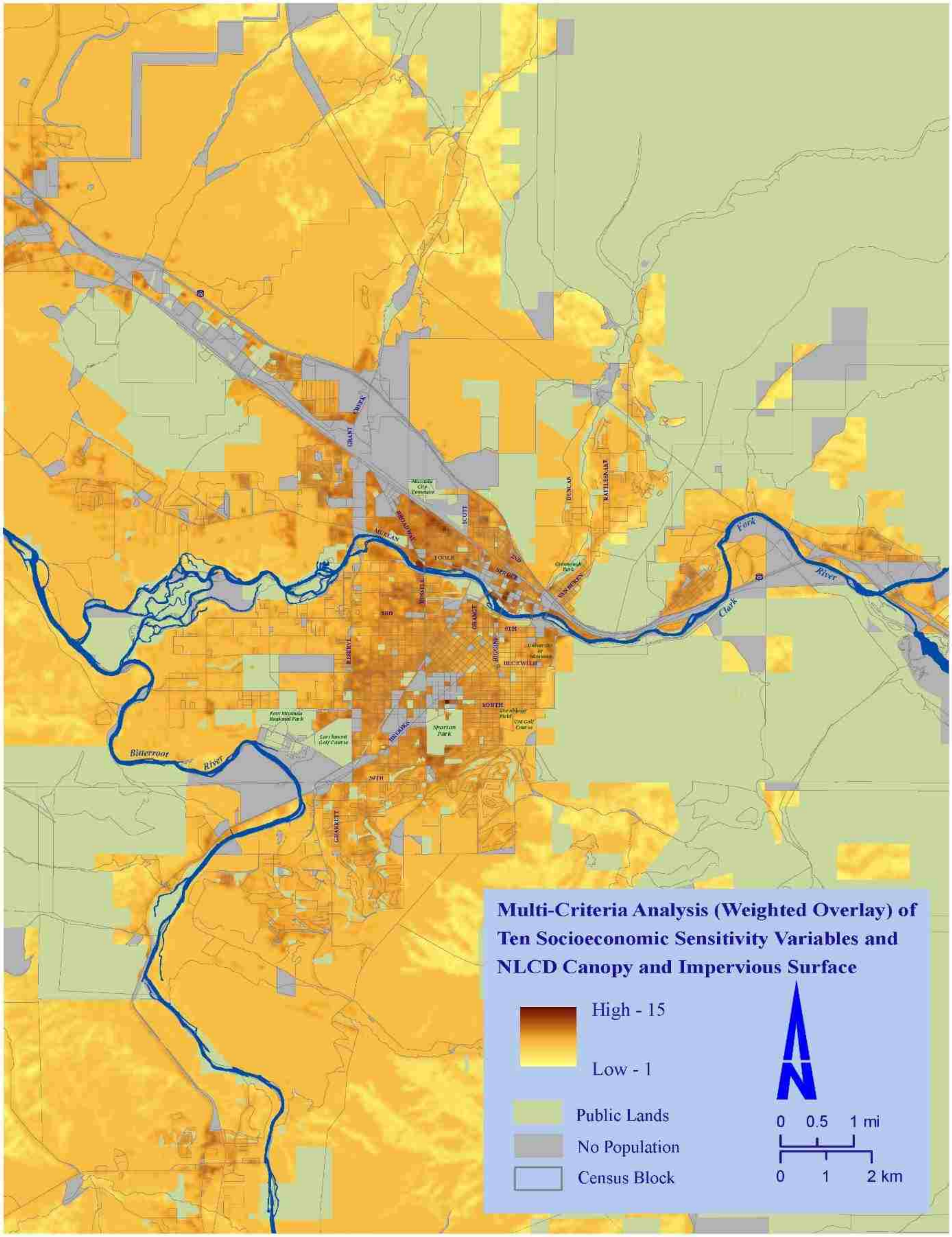

Figure 6: Weighted overlay of the sensitivity layer (Figure 4; 50%) with 2011 NLCD exposure layer (50%).

Figure 5 shows the sensitivity layer (Figure 4) overlaid with LST, each equally weighted to 50%. Figure 6 shows the sensitivity layer (Figure 4) overlaid with the combined 2011 NLCD layer - percentage of impervious surface and percentage of tree canopy - equally weighted to 50%. Weighted overlay is a process in which the pixel values in the classes of the input raster layers are overlaid and combined. The highest score in these two vulnerability overlays does not reach the number of classes (20) of the input exposure layers because the highest score of the sensitivity layer is 11. Figures 5 and 6 display high levels of vulnerability in similar blocks: senior assisted living facilities north of Spartan Park and north of the river on Orange Street, low-income housing north of the river on Russell Street, multi-unit apartments just west of Higgins Avenue downtown, and the Westside neighborhood containing low-income housing and mobile home parks.

In the final overlay in Figure 7, the sensitivity layer is combined equally with the exposure layers LST and NLCD (33% each) to provide the most comprehensive view of where population and households are most vulnerable to heat and smoke. The entire downtown area, bounded by the river to the south and the railroad to the north, as well as the neighborhoods further north and west, show predominantly vulnerable blocks. It is notable there is no ranking below 2, which means that despite socioeconomic variables skewing toward less sensitivity, exposure via high temperatures, increased impervious surface, and lack of canopy have created conditions within city limits where everyone is impacted by heat and smoke – at some level. The blocks displaying darkest/most sensitive in previous overlays are still mapped as the most vulnerable.

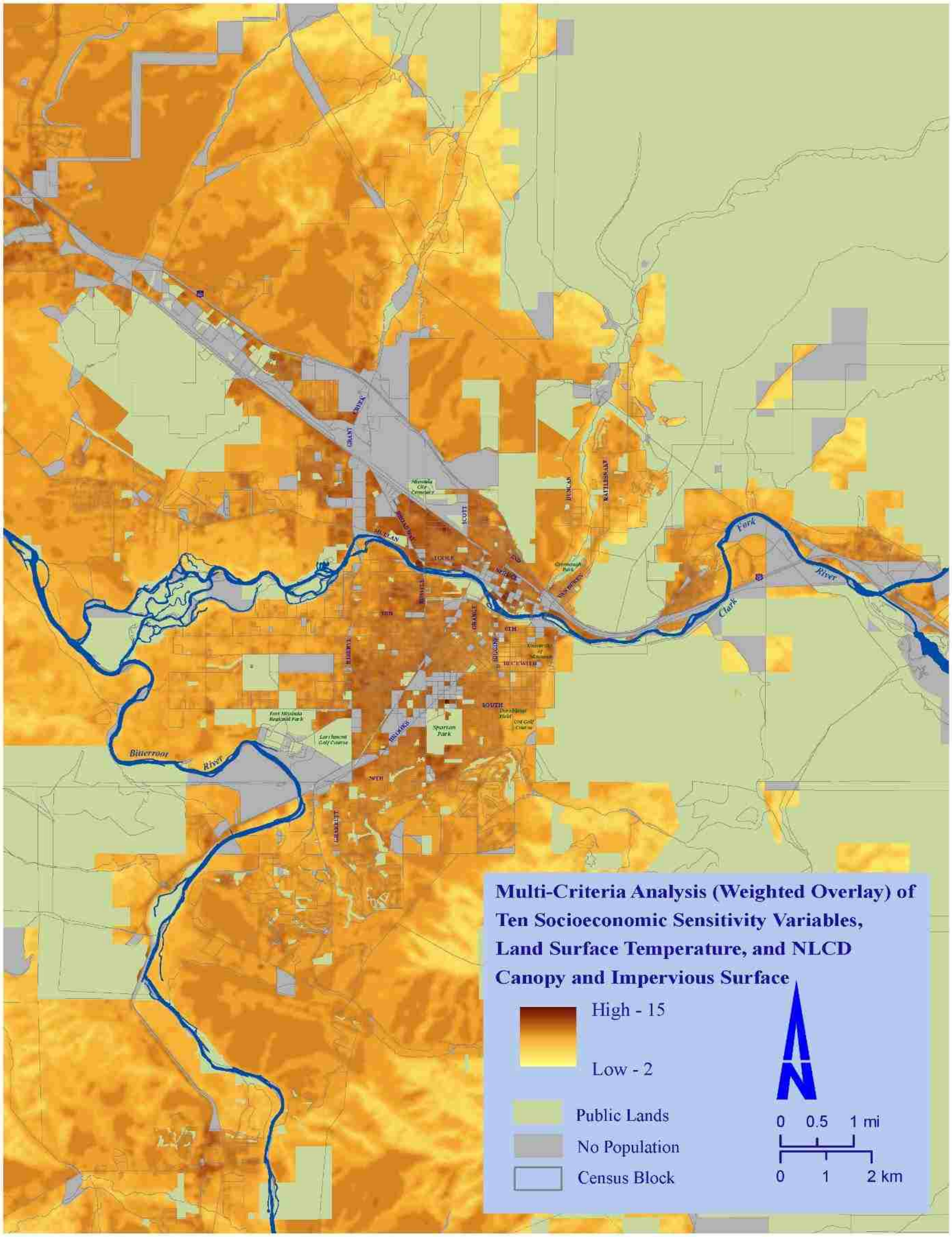

Figure 7: Weighted overlay of the sensitivity layer (Figure 4; 33%) with LST (33%) and 2011 NLCD (33%) exposure layers.

Conclusions and Future Work

This study was facilitated by the American Geophysical Union's Thriving Earth Exchange (TEX) and is a result of collaboration between national, state, and local stakeholders seeking to create a robust plan for climate mitigation and adaptation in Missoula. The initial objective was to produce a map of Missoula's urban heat island and make recommendations for city government of best practices for mitigating UHI impacts on vulnerable populations. However, the study turned to determining who and where those people were in Missoula.

When social sensitivity is mapped contemporaneously with exposure, the result depicts where vulnerable populations may be disproportionately affected by a hazard. The inclusion of maps of each indicator provides further understanding of how the weighted overlay method was constructed, and areas to be considered for prioritization in planning. The type of conclusions based upon specific social, economic, or exposure data, are to some extent limited in the specificity that can be drawn for an individual mapping unit. However, this does allow assessment of the range of conditions present in the community (and thus the types of interventions which should be considered) and provides a rough spatial estimate of where interventions might be needed most.

This assessment drew upon studies that have combined socioeconomic and exposure variables to portray vulnerability but was performed at an unusually fine spatial resolution. The inclusion of air quality data was of local concern and added as project objectives were being refined. The two-fold environmental hazard of heat and smoke brought on by a warming climate in the western U.S. is a growing concern. People impacted by these conditions confront multiple challenges in making their home environment comfortable and healthy. In cities the size of

Missoula, surveys to ascertain whether homes have air conditioning and filtration systems are rare and should be expanded.

Although conditions such as asthma, diabetes, and cardiopulmonary and respiratory disease have been shown to be exacerbated by extreme heat (Managan et al. 2014) and poor air quality (Rappold et al. 2012), the coarse scale of the available data prohibited inclusion of health outcomes in this assessment. While the CDC's Behavioral Risk Factor Surveillance System is the data source for most vulnerability studies that include health data, the census tract scale and coarse geospatial information for survey respondents did not allow interpolating to relatively fine-scale census block groups or blocks. Localized data collection on health indicators linked to heat and smoke would allow analysis that could reveal which factors are of most impact to residents.

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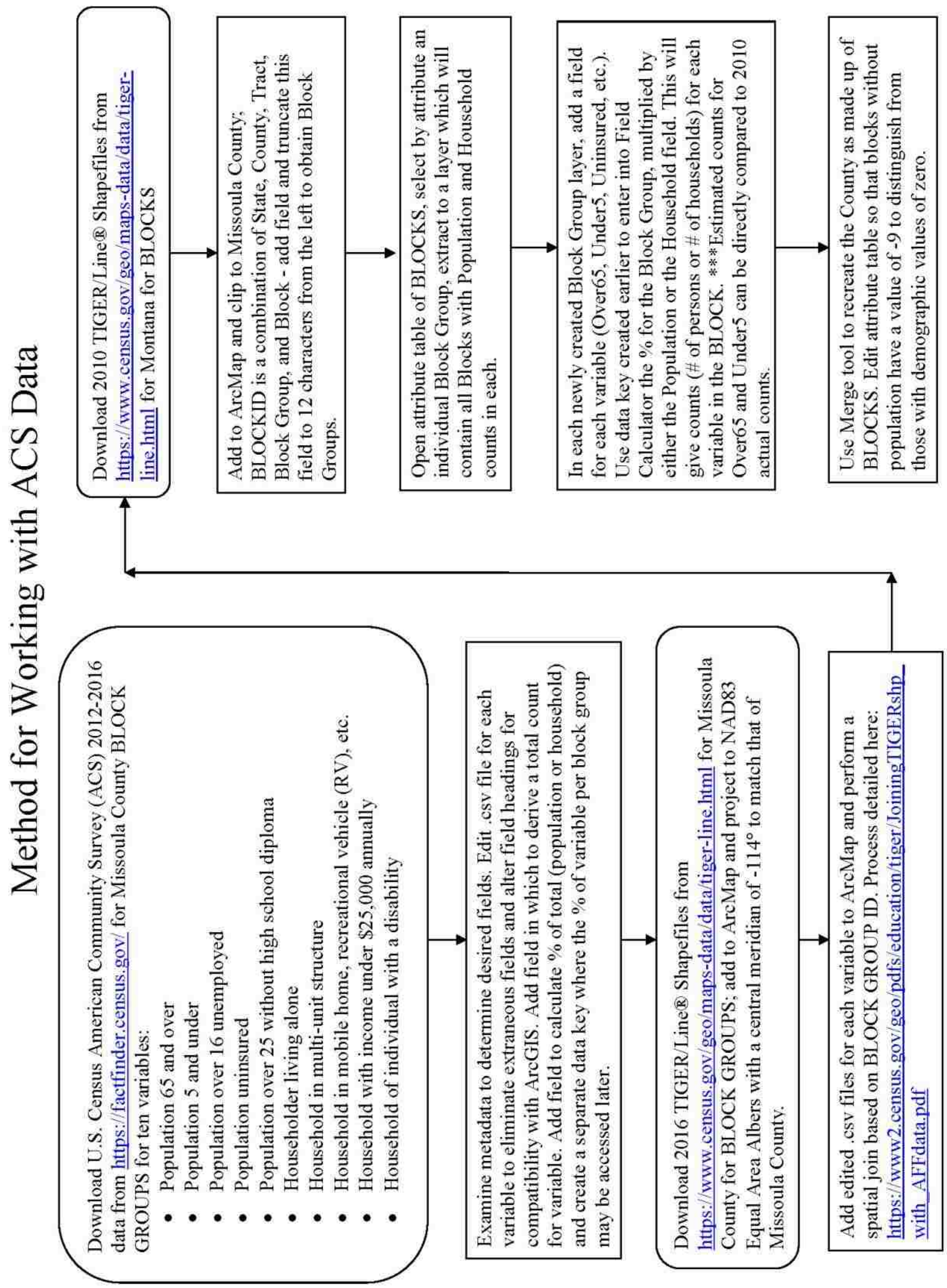
Appendix A: Method for Working with ACS Data



Appendix B: Method for Working with MCA

Method for Working with Multi-Criteria Analysis (MCA)

The ACS data workflow should result in Missoula County BLOCK map containing data for ten variables:

- Population 65 and over
- Population 5 and under
- Population over 16 unemployed
- Population uninsured
- Population over 25 without high school diploma
- Householder living alone
- Household in multi-unit structure
- Household in mobile home, recreational vehicle (RV), etc.
- Household with income under $25,000 annually
- Household of individual with a disability

↓

The ArcMap process for MCA is known as Weighted Overlay. In order to perform a Weighted Overlay, all data layers must be in raster form. Additional calculations to derive density per block must be performed prior to rasterizing polygon layers.

↓

Public lands assumed to be non-residential are used to clip the BLOCK layer to further define density. A public lands cadastral layer is downloaded from the Montana Dept. of Revenue, and the data is examined to find the ownership (city, county, state, federal). Certain public lands such as those owned by the University System may include residential areas.

↓

Once the residential areas are as accurately apportioned as possible, calculate density of population or household by block. Add an area field (Area_SqK) and use Calculate Geometry function in desired units. Add other fields for density of each variable (Over65_SqK) and use Field Calculator equation ([Over65]/[Area_SqK]) to compute.

→

Search ArcMap for the Polygon to Raster. Perform this conversion with each variable. The measure of scale for the raster should consistent with the exposure layer that will later be used in the Weighted Overlay; in this case, it is the Land Surface Temperature (LST) layer at 30m. This raster must be already downloaded to the geodatabase in order to direct the tool to use it.

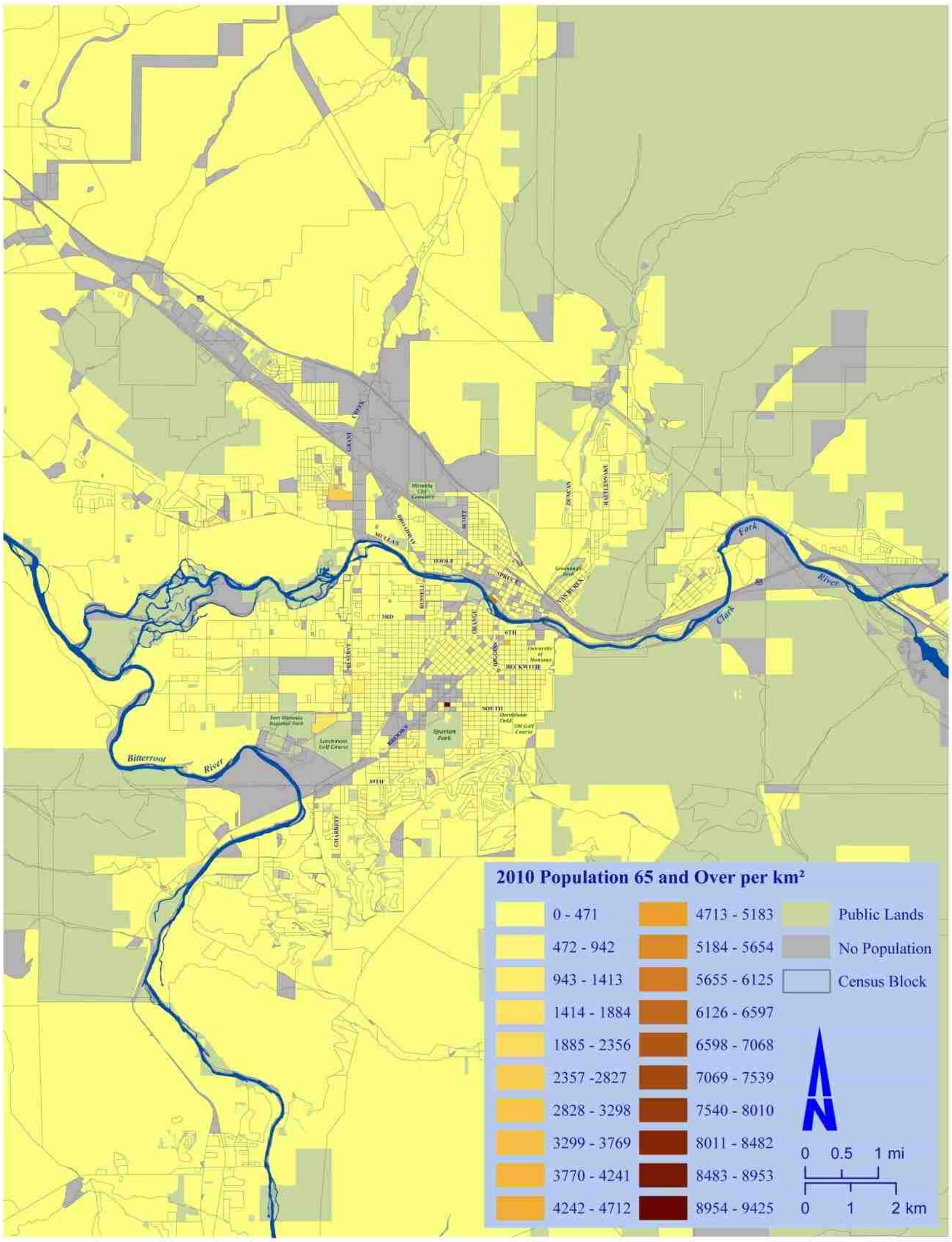
↓

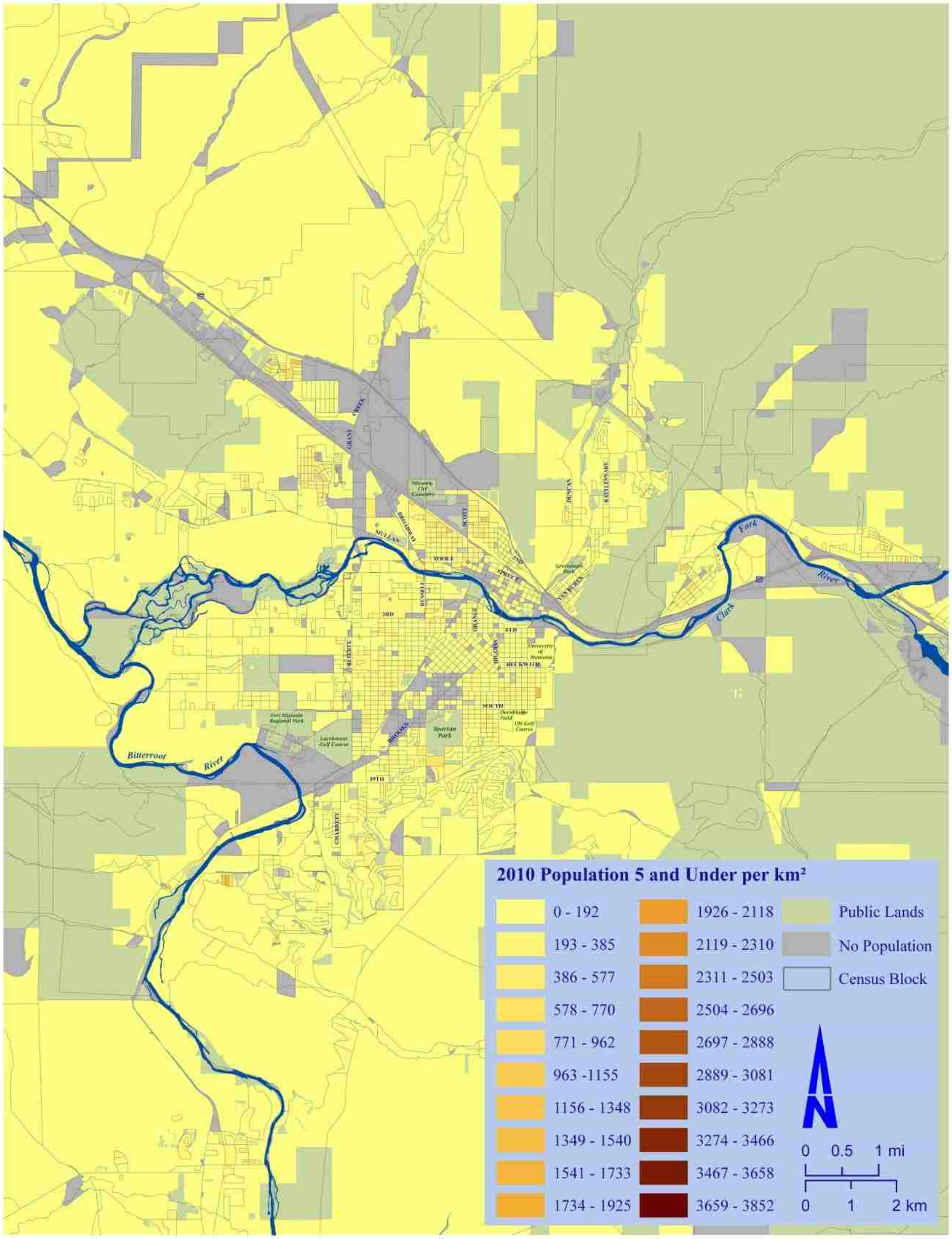
Each raster layer must be reclassified into the same number of categories in the same manner, in order to put each into the Weighted Overlay. Search for the Reclassify tool in ArcMap. Once the input raster is entered, the reclassification chart will display the range of "old" values being placed in each "new" value category. The default is 1-9 but this may be changed by clicking the classify button. In this case, each layer was reclassified to 20 breaks of equal interval. Exposure layers (LST) must also be reclassified to identical standards before being put into a Weighted Overlay. ***In some cases, there will be no data falling in a specific class range.

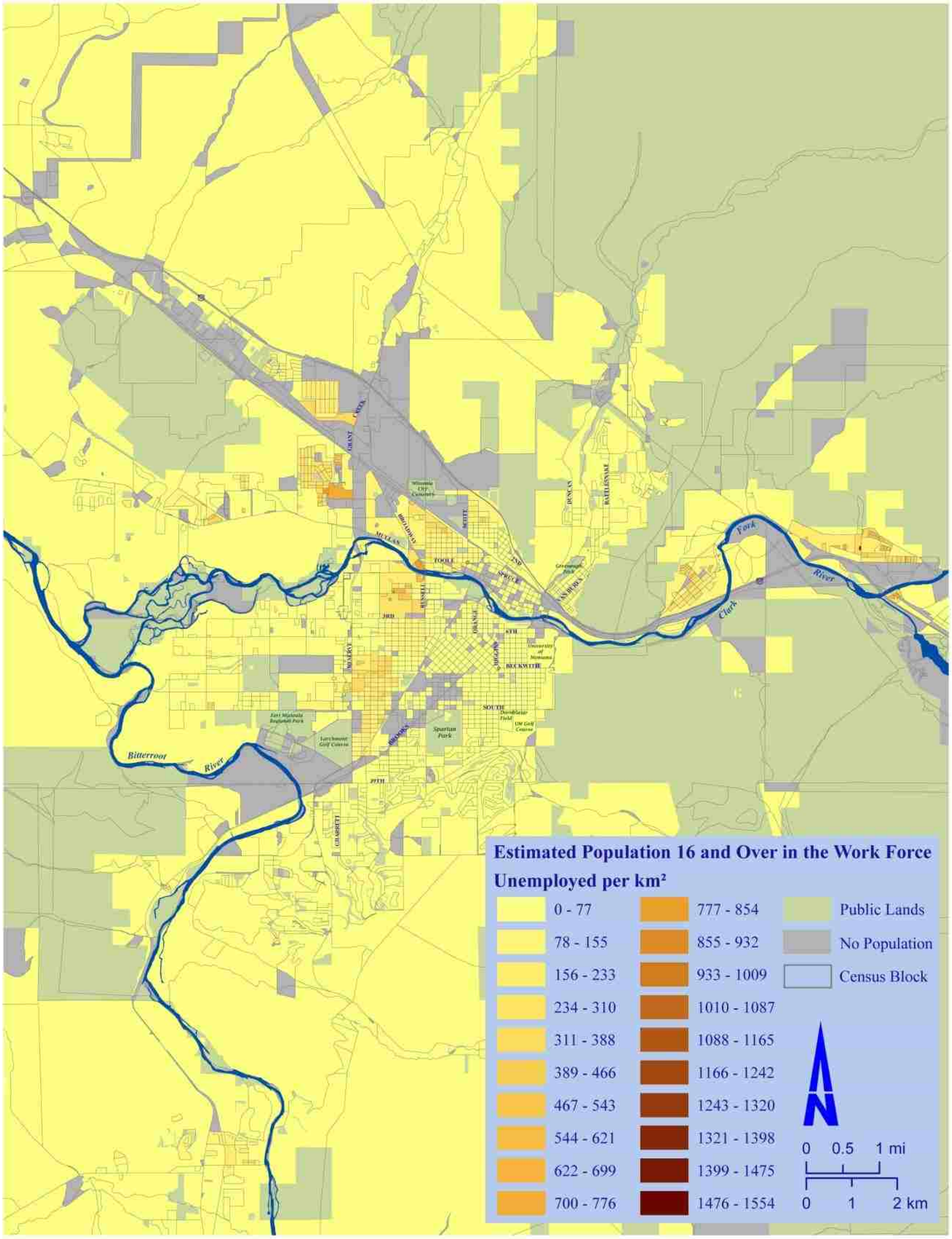
↓

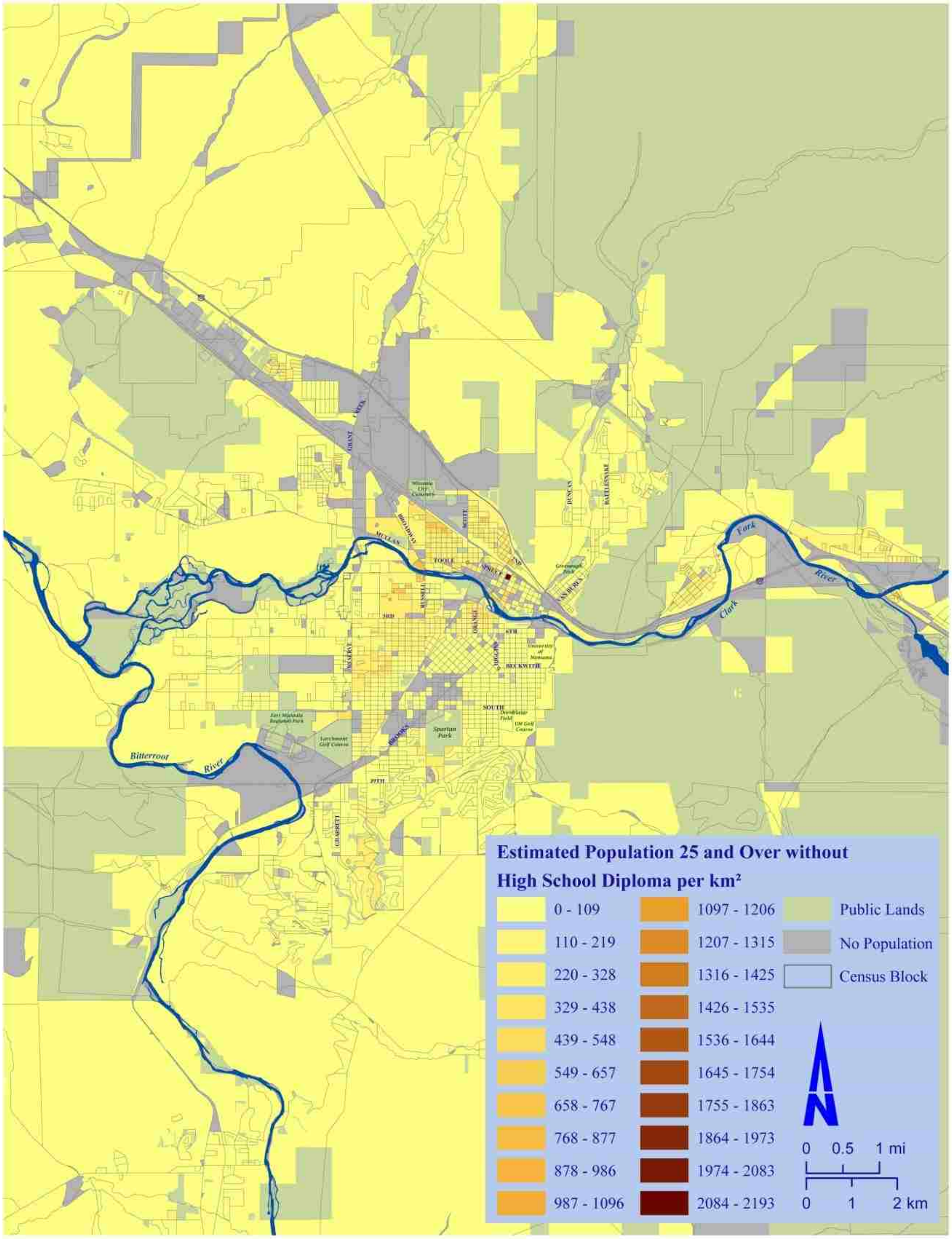
Search for Weighted Overlay tool. In the tool dialog box, set the evaluation scale to reflect the number of classes used in the previous step (in this case 1 to 20 by 1). Once a raster layer is loaded into the weighted overlay table, it will have an editable % of influence and scale value. Clicking the set equal influence button will apportion the weighting equally for each raster. The resulting raster may have fewer classes than 20 due to lack of data in all classes. A second Weighted Overlay can be run on this sensitivity layer and the reclassified exposure raster with equal weights applied.

Appendix C: Sensitivity and Exposure Layers

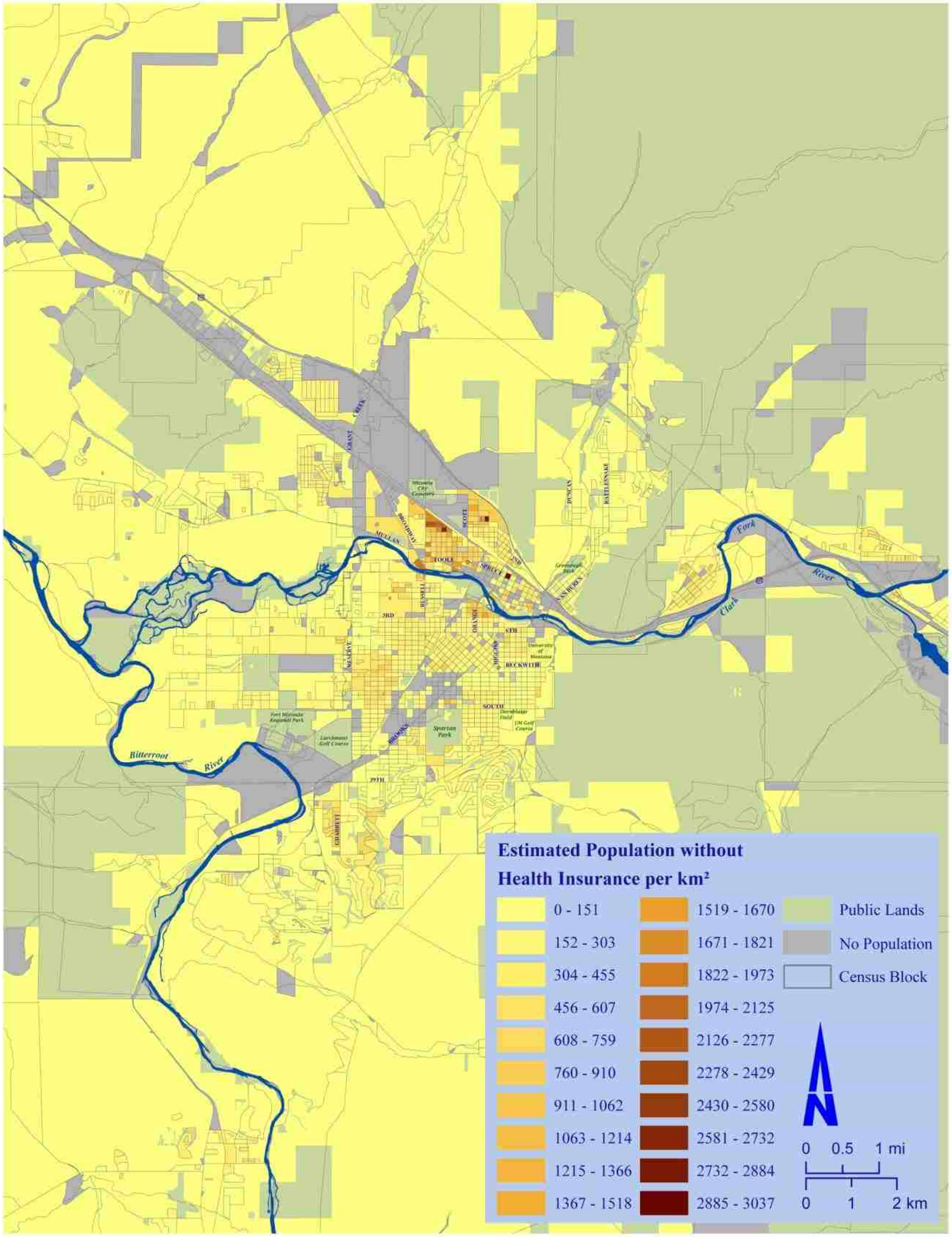


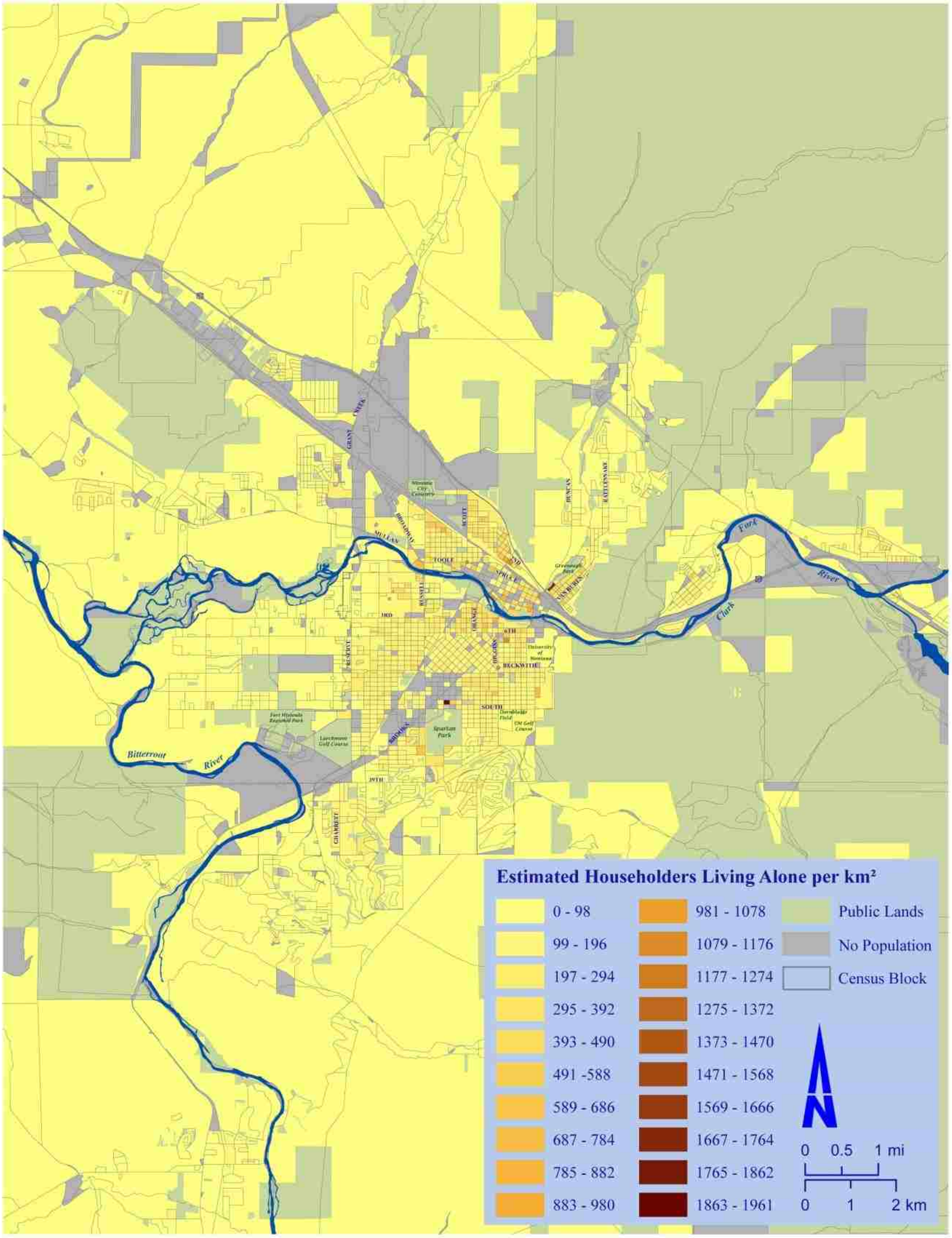

2010 Population 5 and Under per km²
0 - 192
193 - 385
386 - 577
578 - 770
771 - 962
963 -1155
1156 - 1348
1349 - 1540
1541 - 1733
1734 - 1925
1926 - 2118
2119 - 2310
2311 - 2503
2504 - 2696
2697 - 2888
2889 - 3081
3082 - 3273
3274 - 3466
3467 - 3658
3659 - 3852
Public Lands
No Population
Census Block
0 0.5 1 mi
0 1 2 km
Bitterroot River
Clark Fork River

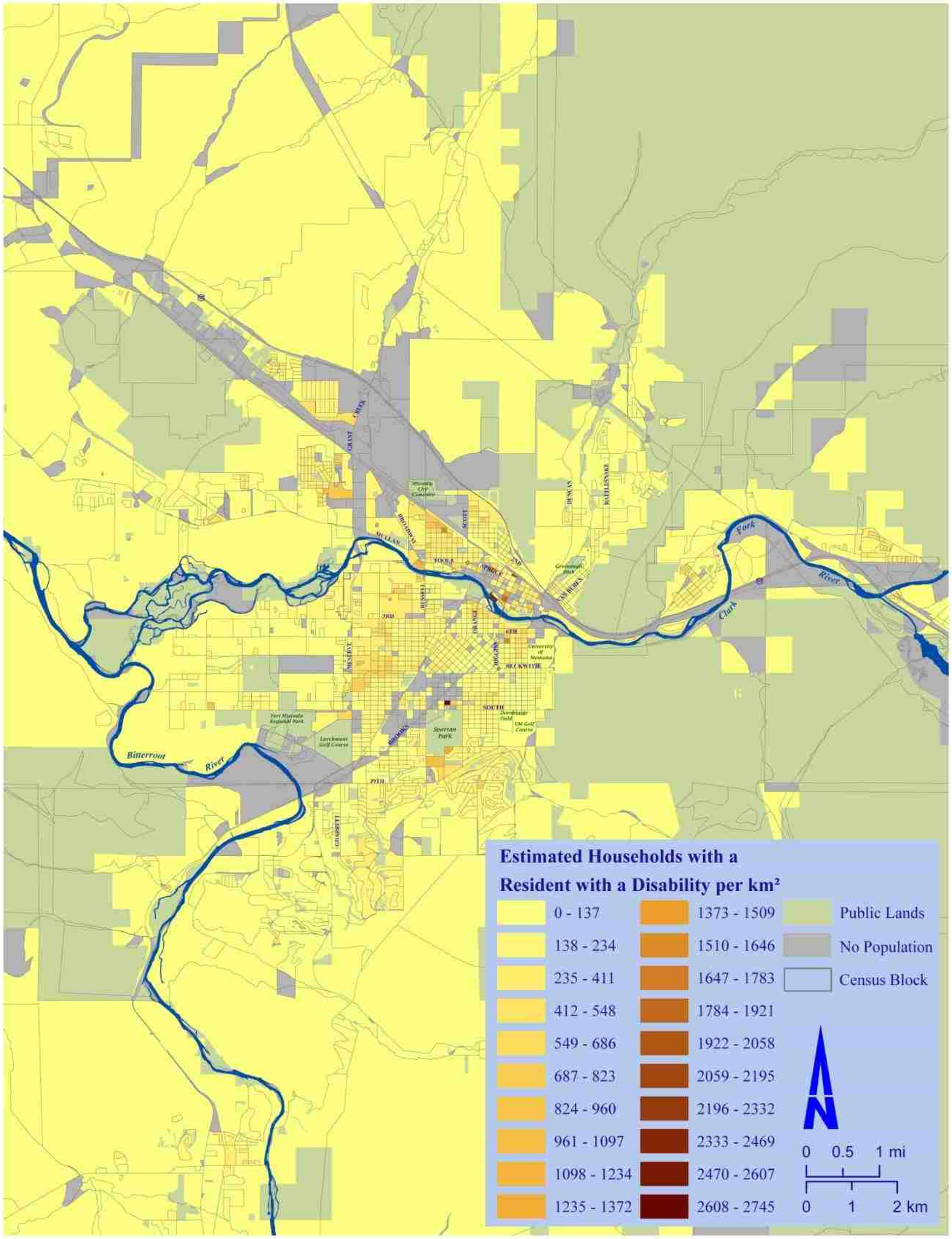

Estimated Population 16 and Over in the Work Force
Unemployed per km²
0 - 77
78 - 155
156 - 233
234 - 310
311 - 388
389 - 466
467 - 543
544 - 621
622 - 699
700 - 776
777 - 854
855 - 932
933 - 1009
1010 - 1087
1088 - 1165
1166 - 1242
1243 - 1320
1321 - 1398
1399 - 1475
1476 - 1554
Public Lands
No Population
Census Block
0 0.5 1 mi
0 1 2 km
Bitterroot
River
Clark
Fork
River

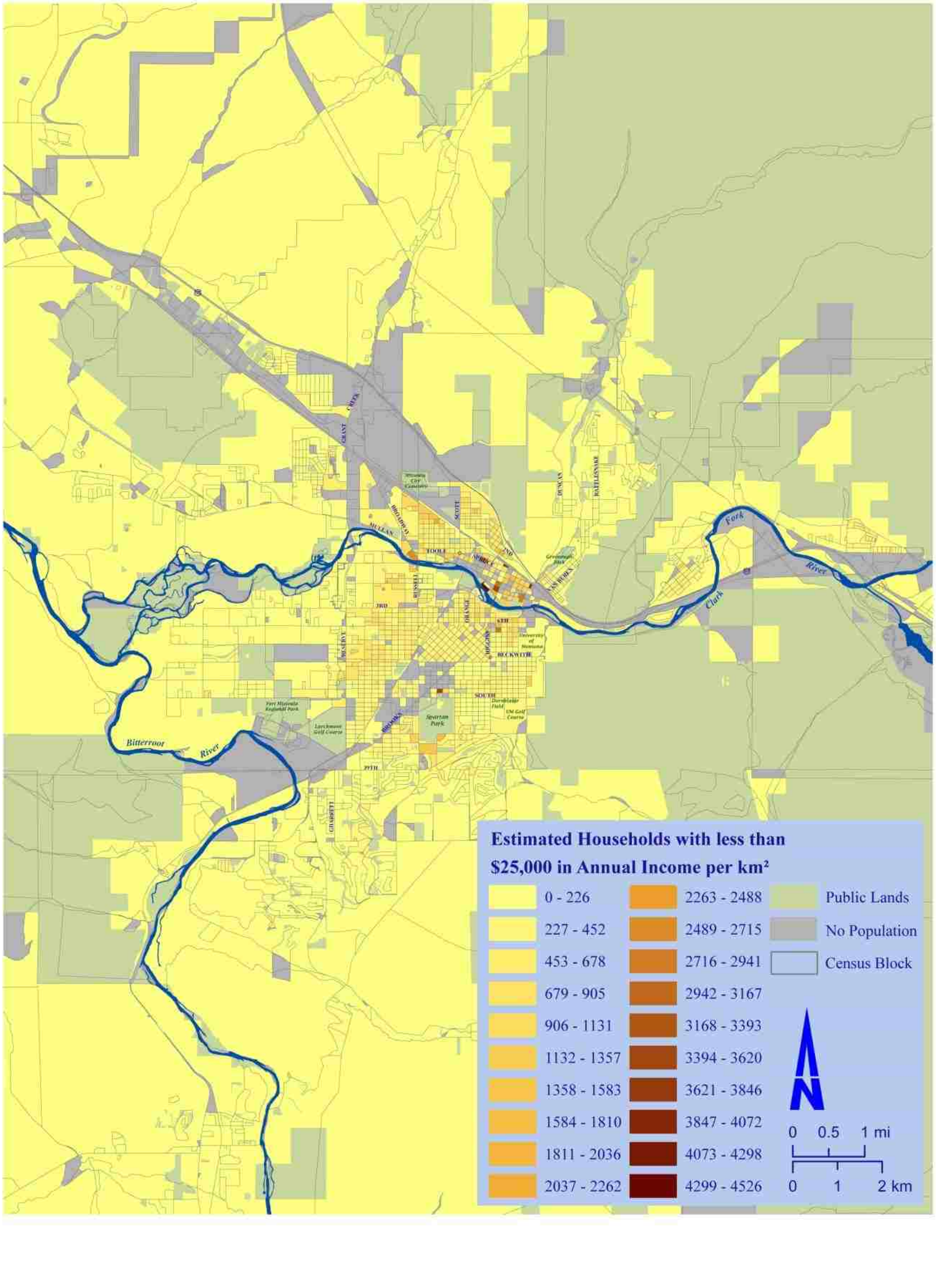


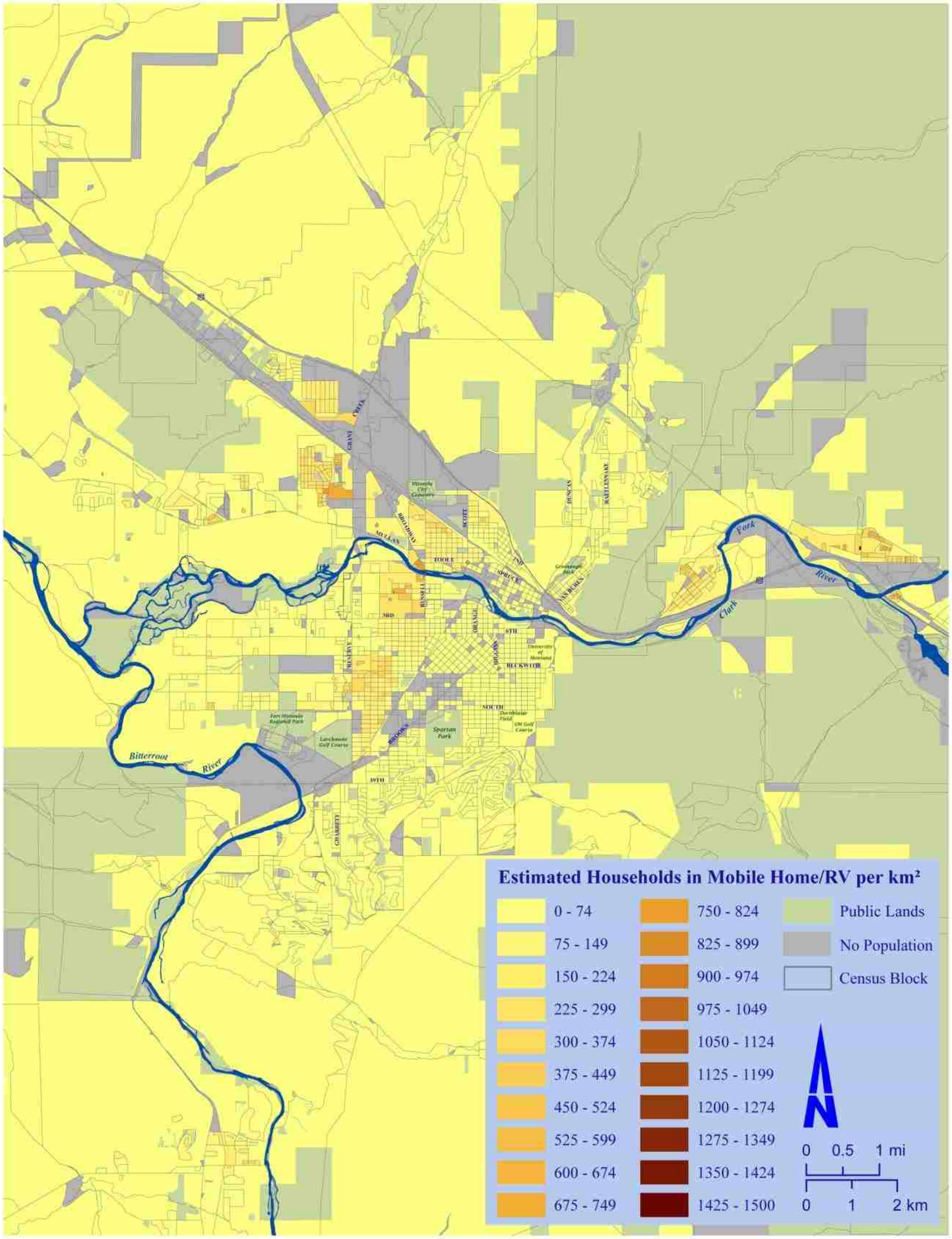
Estimated Population 25 and Over without
High School Diploma per km²
0 - 109
110 - 219
220 - 328
329 - 438
439 - 548
549 - 657
658 - 767
768 - 877
878 - 986
987 - 1096
1097 - 1206
1207 - 1315
1316 - 1425
1426 - 1535
1536 - 1644
1645 - 1754
1755 - 1863
1864 - 1973
1974 - 2083
2084 - 2193
Public Lands
No Population
Census Block
0 0.5 1 mi
0 1 2 km
Bitterroot River
Clark Fork River

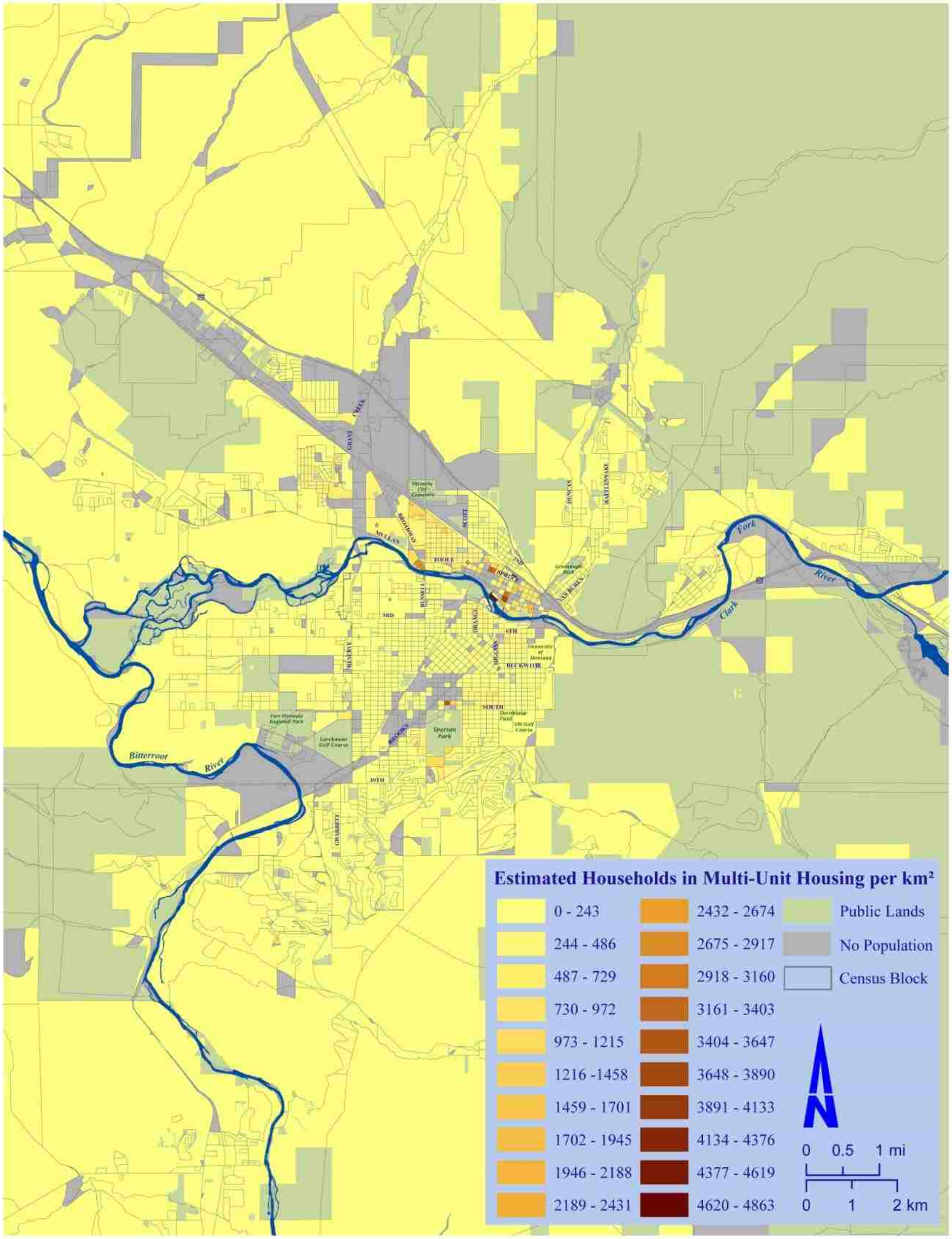

Estimated Population without
Health Insurance per km²
0 - 151
152 - 303
304 - 455
456 - 607
608 - 759
760 - 910
911 - 1062
1063 - 1214
1215 - 1366
1367 - 1518
1519 - 1670
1671 - 1821
1822 - 1973
1974 - 2125
2126 - 2277
2278 - 2429
2430 - 2580
2581 - 2732
2732 - 2884
2885 - 3037
Public Lands
No Population
Census Block
0 0.5 1 mi
0 1 2 km
Bitterroot
River
Clark
Fork
River
Spartan Park
BROADWAY
SCOTT
MULLAN
TOOLE
SPRUCE
BECKWITH
SOUTH
REGENT

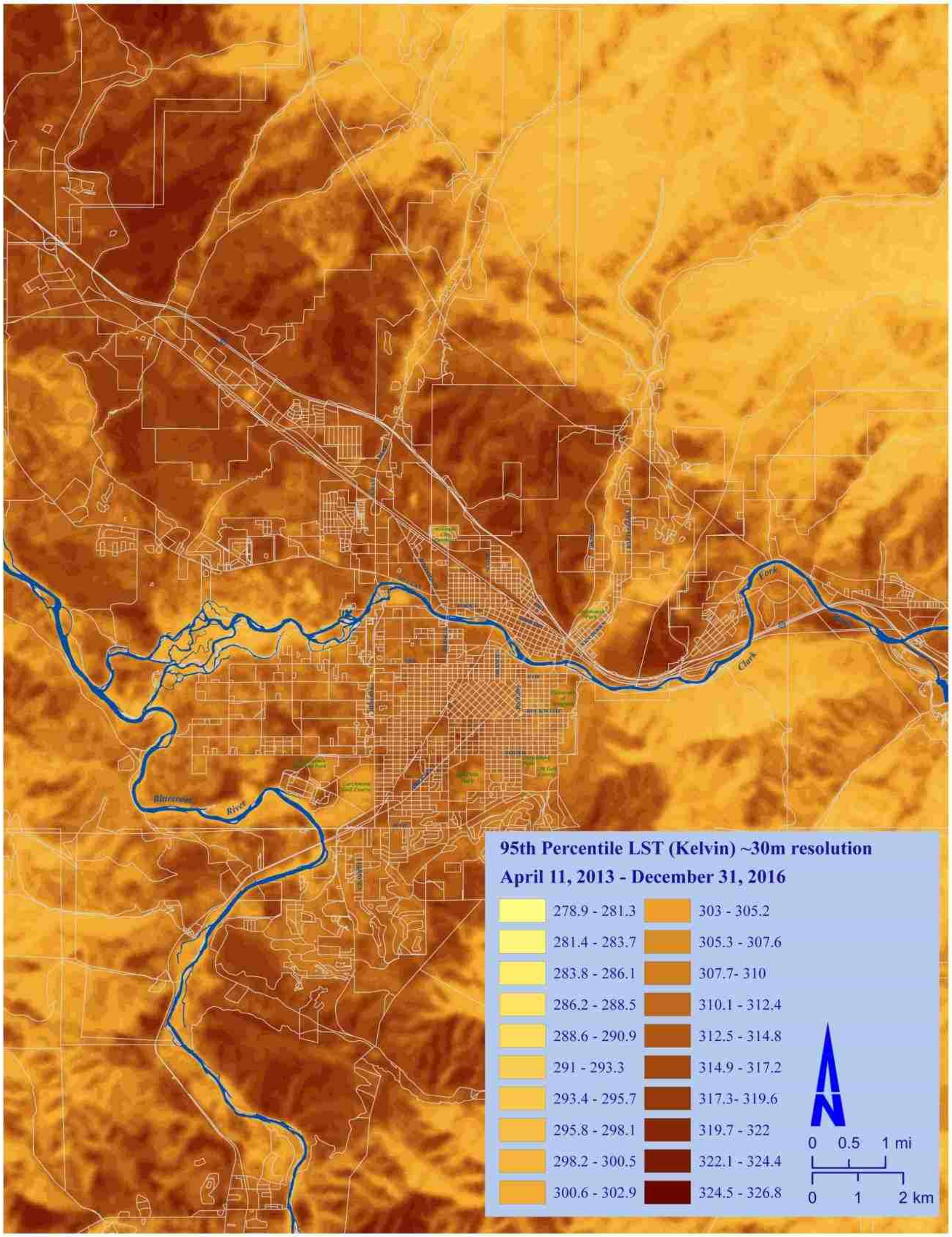

Estimated Householders Living Alone per km²
0 - 98
99 - 196
197 - 294
295 - 392
393 - 490
491 -588
589 - 686
687 - 784
785 - 882
883 - 980
981 - 1078
1079 - 1176
1177 - 1274
1275 - 1372
1373 - 1470
1471 - 1568
1569 - 1666
1667 - 1764
1765 - 1862
1863 - 1961
Public Lands
No Population
Census Block
0 0.5 1 mi
0 1 2 km
Bitterroot
River
Clark
Fork
River

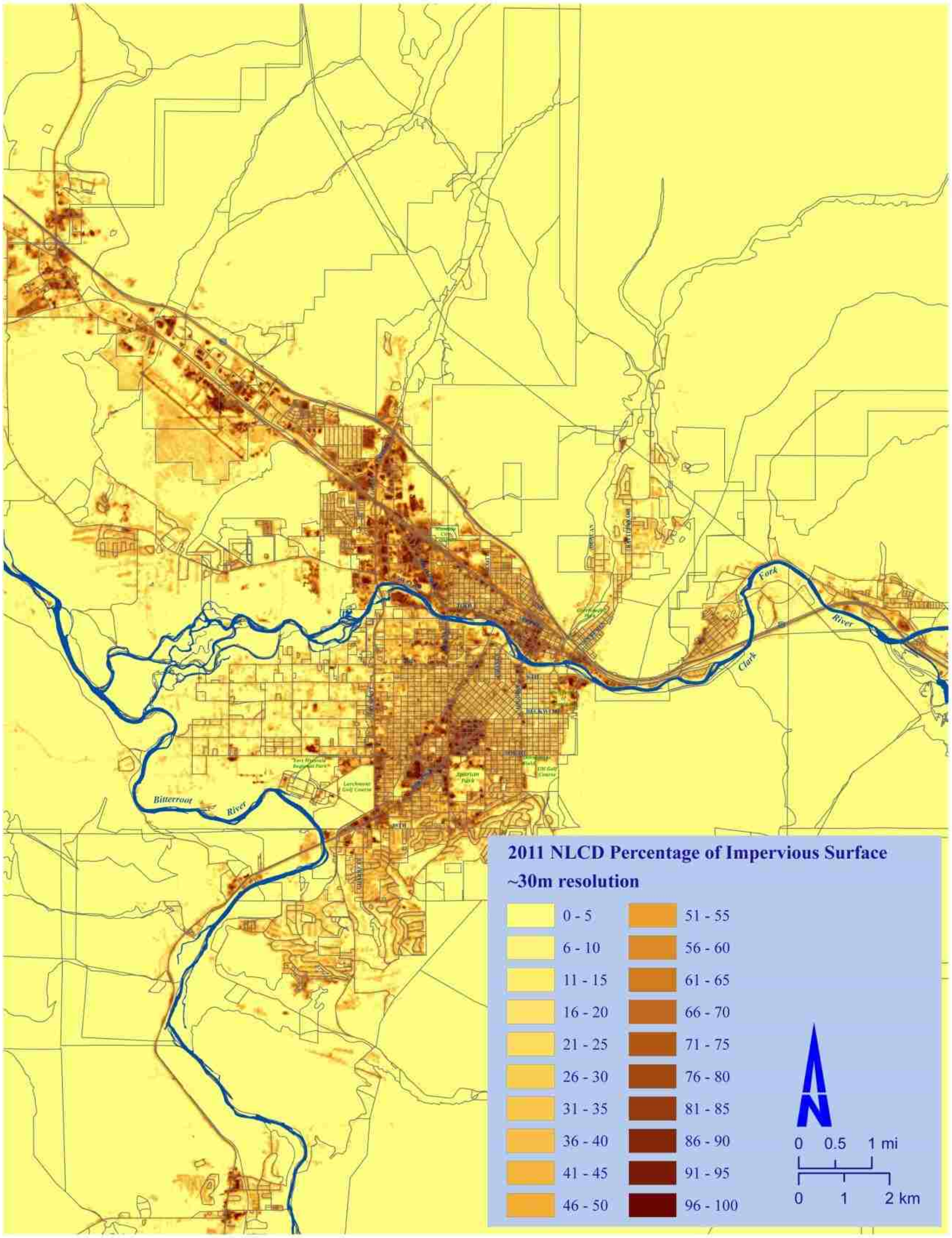

Estimated Households with a Resident with a Disability per km²
0 - 137
138 - 234
235 - 411
412 - 548
549 - 686
687 - 823
824 - 960
961 - 1097
1098 - 1234
1235 - 1372
1373 - 1509
1510 - 1646
1647 - 1783
1784 - 1921
1922 - 2058
2059 - 2195
2196 - 2332
2333 - 2469
2470 - 2607
2608 - 2745
Public Lands
No Population
Census Block
0 0.5 1 mi
0 1 2 km
Bitterroot River
Clark Fork River

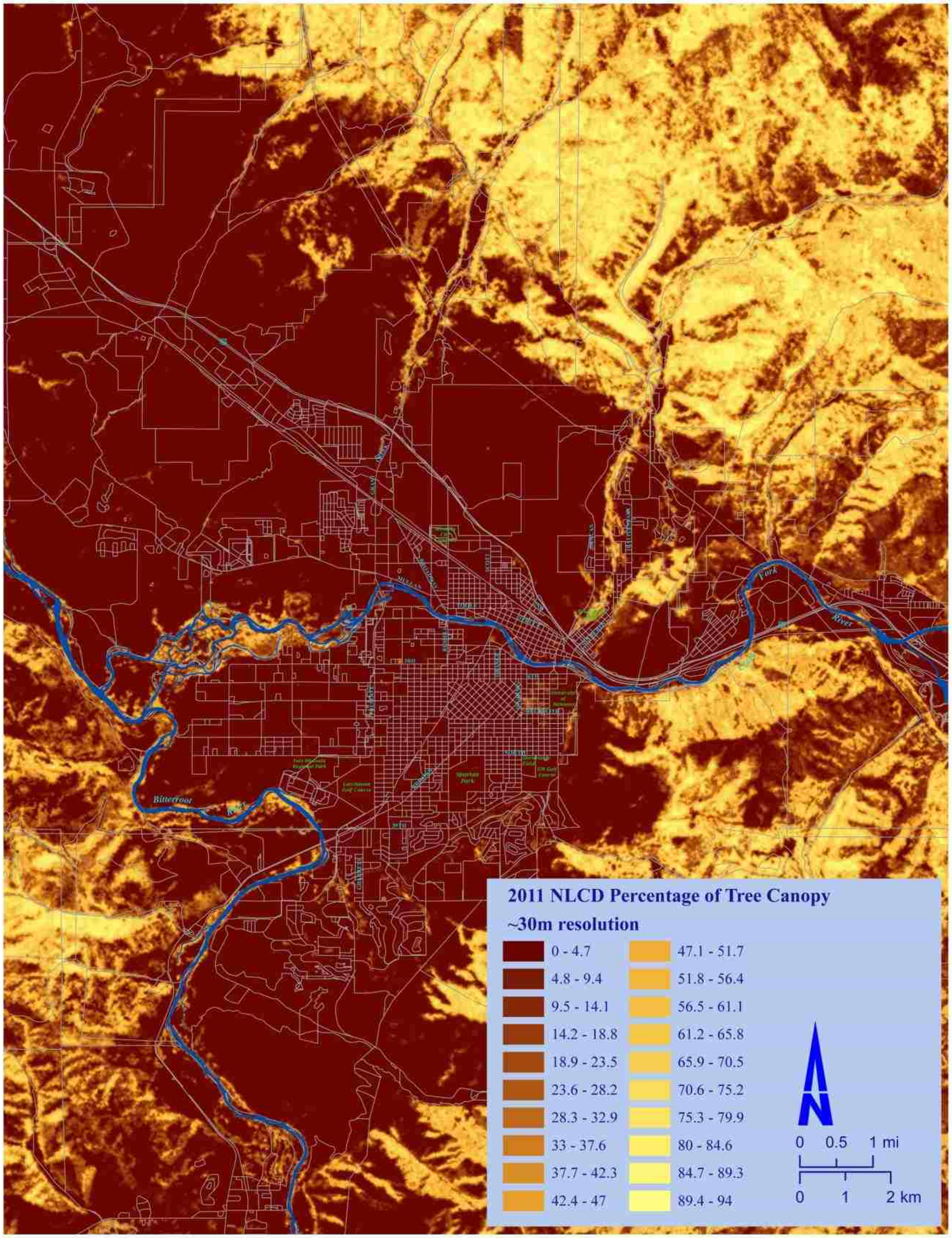

Estimated Households with less than
$25,000 in Annual Income per km²
0 - 226
227 - 452
453 - 678
679 - 905
906 - 1131
1132 - 1357
1358 - 1583
1584 - 1810
1811 - 2036
2037 - 2262
2263 - 2488
2489 - 2715
2716 - 2941
2942 - 3167
3168 - 3393
3394 - 3620
3621 - 3846
3847 - 4072
4073 - 4298
4299 - 4526
Public Lands
No Population
Census Block
N
0 0.5 1 mi
0 1 2 km
Bitterroot River
Clark Fork River


Estimated Households in Mobile Home/RV per km²
0 - 74
75 - 149
150 - 224
225 - 299
300 - 374
375 - 449
450 - 524
525 - 599
600 - 674
675 - 749
750 - 824
825 - 899
900 - 974
975 - 1049
1050 - 1124
1125 - 1199
1200 - 1274
1275 - 1349
1350 - 1424
1425 - 1500
Public Lands
No Population
Census Block
0 0.5 1 mi
0 1 2 km
Bitterroot River
Clark Fork River


Estimated Households in Multi-Unit Housing per km²
0 - 243
244 - 486
487 - 729
730 - 972
973 - 1215
1216 -1458
1459 - 1701
1702 - 1945
1946 - 2188
2189 - 2431
2432 - 2674
2675 - 2917
2918 - 3160
3161 - 3403
3404 - 3647
3648 - 3890
3891 - 4133
4134 - 4376
4377 - 4619
4620 - 4863
Public Lands
No Population
Census Block
N
0 0.5 1 mi
0 1 2 km
Bitterroot
River
Clark
Fork
River


95th Percentile LST (Kelvin) ~30m resolution
April 11, 2013 - December 31, 2016
278.9 - 281.3
281.4 - 283.7
283.8 - 286.1
286.2 - 288.5
288.6 - 290.9
291 - 293.3
293.4 - 295.7
295.8 - 298.1
298.2 - 300.5
300.6 - 302.9
303 - 305.2
305.3 - 307.6
307.7- 310
310.1 - 312.4
312.5 - 314.8
314.9 - 317.2
317.3- 319.6
319.7 - 322
322.1 - 324.4
324.5 - 326.8
N
0 0.5 1 mi
0 1 2 km
Bitterroot River
Clark Fork


2011 NLCD Percentage of Impervious Surface
~30m resolution
0 - 5
6 - 10
11 - 15
16 - 20
21 - 25
26 - 30
31 - 35
36 - 40
41 - 45
46 - 50
51 - 55
56 - 60
61 - 65
66 - 70
71 - 75
76 - 80
81 - 85
86 - 90
91 - 95
96 - 100
0 0.5 1 mi
0 1 2 km
Bitterroot
River
Clark
Fork
River



2011 NLCD Percentage of Tree Canopy
~30m resolution
0 - 4.7
4.8 - 9.4
9.5 - 14.1
14.2 - 18.8
18.9 - 23.5
23.6 - 28.2
28.3 - 32.9
33 - 37.6
37.7 - 42.3
42.4 - 47
47.1 - 51.7
51.8 - 56.4
56.5 - 61.1
61.2 - 65.8
65.9 - 70.5
70.6 - 75.2
75.3 - 79.9
80 - 84.6
84.7 - 89.3
89.4 - 94
0 0.5 1 mi
0 1 2 km
Bitterroot
River