INCORPORATING SPATIO-TEMPORAL DEMOGRAPHIC CHANGES IN HEAT WAVE RELATED FUTURE VULNERABILITY ASSESSMENT

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MARCH, 2017

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ABSTRACT

There is an emerging concern in regards to the exclusion of socioeconomic changes in future climate change vulnerability studies. This study addressed this gap by developing an approach to incorporate socioeconomic changes focusing on the demographic change in the context of urban heat wave issue. Hence, the combination of population projection, land use model and dasymetric mapping were proposed to capture the population composition change and population density change as the selected demographic data that matter to assess urban vulnerability to heat wave in the future. Using produced data from the proposed method, this study highlights the effect of demographic changes for future vulnerability within intra urban scale, grid level vulnerability assessment method was applied using Oklahoma City as the Case study. This study revealed the importance of incorporating that that demographic changes will lead to different vulnerability condition in the future. The change of population composition contributes in giving insight about the future sensitivity as it shows the changes of vulnerable group population numbers. Meanwhile, the projected population density that might happen under various urban development scenario and population projection scenarios show that the exposure to heat wave will increase in terms of quantity and area extent in the future. All in all, this information provides a meaningful insight regarding vulnerable areas in the future including its demographic drivers, thus supporting authority and policy maker to deliver better climate change adaptation measures.

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LIST OF ABBREVIATIONS

CA	Cellular Automata
CC	Climate Change
GHG	Green House Gas
GIS	Geo Information System
IPCC	Intergovernmental Panel on Climate Change
LC	Land Cover
LU	Land Use
LUC	Land Use Change
LUTA	Land Use Typology
PCA	Principal Component Analysis
PPS	Population Projection Scenario
RCP	Representative Concentration Pathway
SSP	Shared Socioeconomic Pathway
TM	Thematic Mapper
UHI	Urban Heat Island
UTM	Universal Transverse Mercator
USA	United States of America

1. INTRODUCTION

The introductory chapter provides the foundation of the study. It starts with the identification of emerging issues in climate change domain leading to the formulation of the research problem. This research problem is then outlined into research objectives and research questions presented as the closing of this chapter.

1.1. Background

Climate Change (CC) is a global phenomenon currently happening on the globe. It is defined as "a change in the state of climate that can be identified (e.g. using statistical tests) by change in the mean and /or the variability of its properties, and that persists for an extended period, typically decades or longer" (IPCC, 2007b, Glossary, pg. 78). This phenomenon is attributed to the increase in the emission of Greenhouse Gas (GHG) mainly due to anthropogenic activities such as infrastructure development, land use changes, etc. (UN-REDD, 2009). In recent decades, changes in the climate have caused impacts on all region throughout the globe. Some of the significant impacts are including the changing precipitation, rising global temperature, melting ice caps, and rising occurrence of extreme events (IPCC, 2014). The impacts coming from the climate-related extremes such as heat waves, droughts, floods, cyclones and wildfires, create a certain degree of vulnerability of the human systems to current climate variability (IPCC, 2014).

The word 'vulnerability' explains the condition of a system which is likely to experience harm due to exposure to a hazard (Turner 2nd et al., 2003). It is as a broad concept which incorporates various dimensions such as social, cultural, physical, and structural (Aubrecht, 2012). Vulnerability also refers to the factors determining a system's ability to withstand and recover from stress or perturbation which mainly focus on intrinsic characteristics of population (e.g., age, sex, socioeconomic status, ethnicity, livelihood strategies) (de Sherbinin, 2014). From a climate change perspective, IPCC defined vulnerability as "The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes" (IPCC, 2001). To the human system, the degree of vulnerability relies upon the exposure of stress/perturbation to the socioeconomic condition of the population.

The dynamic condition of climate and human system would lead to a different vulnerability in the future. First, climate change impacts are expected to be more severe in the end of 21st century due to the more precarious global warming (IPCC, 2013). It is expected that this condition would lead to more vulnerability of human system. On the other hand, the human system itself is also changing throughout the years due to many reasons such as economic development, natural disaster occurrence, urbanization and other drivers. Consequently, this change could also lead to a changing degree of human system vulnerability in the upcoming years. All in all, this condition points out the need to address the vulnerability to the climate change impacts in the future.

In the global context, scholars in climate change community have tried to address this issue by developing future climate scenarios namely Representative Concentration Pathways (RCPs) and future socio-economic scenarios called Shared Socio-economic Development Pathways (SSPs). The RCPs set the foundation of trajectories for climate modelling experiment (Van Vuuren et al., 2011) that is used in the climate-related research. Meanwhile, SSPs serves as "plausible alternative trends in the evolution of society and natural systems over the 21st century at the level of the world and large world regions, which consist of two elements: a narrative storyline and a set of quantified measures of development" (O'Neill et al., 2014 pg.

384). Currently, these scenarios are being the central discussion among the scholars in climate change community as a mean to characterize the future vulnerability.

To get a better insight about vulnerability condition in the future, it is also necessary to characterize the future vulnerability through vulnerability assessment. Within the domain of climate change, assessment of vulnerability serves the purpose of increasing scientific understanding of climate-sensitive systems, informing the targets for the climate change mitigation, prioritizing political and research efforts to particularly vulnerable sectors and regions, and developing adaptation strategies that reduce climate-sensitive risks (Fussel & Klein, 2006). To reflect the dynamic nature of vulnerability, climate change scholars have tried to enhance the vulnerability studies by incorporating the possibility of changes within climate and socioeconomic system. Following this initiative, much work has been carried out in terms of addressing the future climatic conditions (i.e. Amengual et al. (2014), Heaviside et al. (2016), Huang et al. (2011)) but very little has been done in incorporating the future socioeconomic condition (i.e. Lemonsu et al. (2015)). Therefore, it is necessary to conduct further study to address this shortcoming.

1.2. Research Problem

One of the most prominent climate change impacts is regarding the occurrence of extreme events particularly heat wave. Heat wave is associated with "particularly hot sustained temperatures have been known to produce notable impacts on human mortality, regional economies, and ecosystems"(Meehl & Tebaldi, 2004, pg. 994). Due to the concentration of population, urban areas area experiencing significant impact of this climate phenomenon. Heat-related problem in urban areas is also more severe because mostly high temperature reached during heat waves is often exacerbated by urban heat island (UHI) effect (Basara et al., 2010). UHI refers to the condition where slow cooling of built environment causes the urban core to be warmer at night compared to rural areas (Stewart & Oke, 2012). Due to UHI, the urban areas could be 1−3 °C warmer (on average) than their rural surroundings during the daytime and potentially up to 12 °C warmer at night (Stewart & Oke, 2012). This condition makes the urban population being in the threat of heat-stress which is experienced differently for each person (i.e. some people have already heat stress in warmer temperature even without a heat wave). Nevertheless, regarding the CC impact, heat wave is still the main heat-related issue affecting the daily life of the human population in urban areas. Hence, urban areas deserve to be the focus regarding future heat related vulnerability study.

Furthermore, urban areas are dynamic and changes happen to the physical and socioeconomic condition. These changes, particularly the socioeconomic changes are key determinants of most climate change impacts, potential adaptations and vulnerability (Malone & La Rovere, 2005). As reported in the IPCC AR4 (2007), it is suggested to use five elements to characterize socioeconomic condition: demographic, economic, natural resource use, governance and policy, and cultural. Attention is pointed to demographic and it changes in the future as it serves as basic information to investigate the heat wave effect such as mortality to morbidity for current and future condition (Amengual et al., 2014; Costa-Font et al., 2008; Huang et al., 2011; Lutz & Muttarak, 2017). The demographic changes are also essential and often neglected in estimating the climate impacts (mostly due to temporal data availability issue) (Petkova et al., 2016).

To the best of our knowledge, there is no literature that tried to incorporate the demographic change into future vulnerability assessment, particularly regarding the heat wave issues in urban areas This is mostly due to lack of framework and approach on how to integrate socioeconomic change, particularly the demographic change, in future vulnerability assessment. Therefore, this study will address this issue by developing an approach to incorporate the effect of demographic change in heat wave related future vulnerability assessment focusing on urban area.

1.3. Research objectives

The main objective of this research is to develop an approach to incorporate demographic changes in assessing future urban vulnerability to heat stress. This objective is broken down into three specific objectives:

1. To identify the common usage of demographic data in heat urban vulnerability assessment
2. To develop methods to capture demographic changes that matter for future urban vulnerability assessment
3. To identify how the demographic changes could affect future vulnerability to heat wave

1.4. Research Question

Built upon the specific research objectives, research questions were formulated:

1. To identify the usage of demographic data in heat urban vulnerability assessment
    - What are the determinants of urban vulnerability assessment?
    - What are the common demographic data used in assessing urban heat wave vulnerability?
2. To develop methods to capture demographic data changes that matter for future urban heat wave vulnerability assessment
    - What is the difference between current and future vulnerability assessment?
    - What methods appropriate to provide the required data?
3. To identify how the demographic changes could affect future vulnerability to heat wave
    - What is the effect of incorporating future demographic data in future vulnerability assessment practice?

2. LITERATURE REVIEW

This chapter provides a brief literature review of the most important concepts in this study. It covers the basic vulnerability concept and how it is explained in urban heat wave context. It also discusses the relation between demographic data and the vulnerability assessment framework. As summary, the chapter draws the connection between these concepts. It is followed by the proposed approach on incorporating demographic changes into heat wave related future urban vulnerability assessment.

2.1. Urban Heat Vulnerability Framework

Basic knowledge regarding vulnerability concept within climate change domain is important in addressing the heat related climate change impact in urban area. The following section gives an overview regarding CC heat related vulnerability concept within urban context.

2.1.1. Climate Change Vulnerability Concept

IPCC in their Fourth Assessment Report (AR 4) defines vulnerability to climate change as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extreme events. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity" (IPCC , 2007, Glossary). Under this framework, vulnerability comprises of three elements: exposure, sensitivity and adaptive capacity (see Figure 1). Exposure refers to the size of the area and/or system, sector or group affected and the magnitude of the stressor; sensitivity explains the characteristics of a system or population and the governance/market structures that influence the degree to which it is affected by stressors; and adaptive capacity is defined as capacities of the system, sector or group to resist impacts, cope with losses, and/or regain functions (De Sherbinin, 2014).

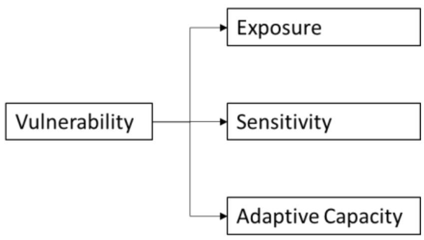


Figure 1 Vulnerability Concept in IPCC Fourth Assessment Report

Source : IPCC (2007)

Through their SREX report (IPCC, 2012), IPCC tries to enhance climate change adaptation effort by incorporating disaster and extreme event management in an integrated framework (see Figure 2). They point out the notion that adverse impacts of climate change can be considered as disasters when they cause damage and severe alterations in the socioeconomic system. The exposure to these adverse climate impacts resembles to the exposure of hazard in natural disaster domain. As an implication, vulnerability can also be described as "the propensity or predisposition to be adversely affected" (IPCC, 2012). This type of vulnerability conceptualization refers to the definition of *contextual vulnerability* which focuses on factors that determine a system's ability to withstand and recover from shocks (resilience).

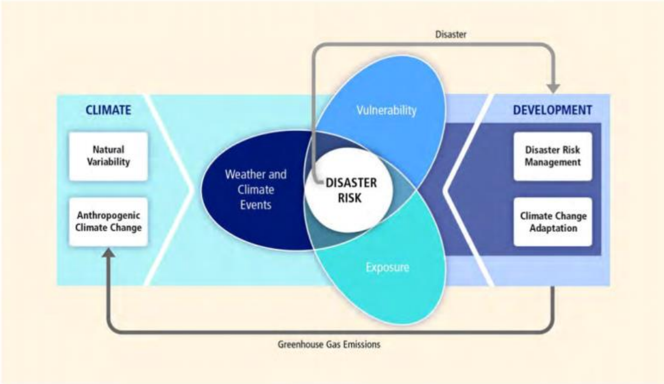


Figure 2 SREX Framework

Source : IPCC (2012)

2.1.2. Urban Heat Wave Vulnerability in Climate Change Vulnerability Framework

Furthermore, Romero-Lankao et al. (2012) present a holistic framework to analyse vulnerability of urban system to the adverse impacts of climate change (Figure 3). Build upon the prior more general vulnerability framework (IPCC 3rd and 4th Assessment), their work perceives urban vulnerability as the potential for people in urban areas to be negatively impacted by climate change. It is a function of 1) hazards (stresses to a system), 2) exposure (i.e., the extent to which urban populations are in exposed with hazards), 3) sensitivity (the degree to which subsets of urban populations are susceptible to hazards), and 4) adaptive capacity (the ability to avoid or lessen the negative consequences of climate change).

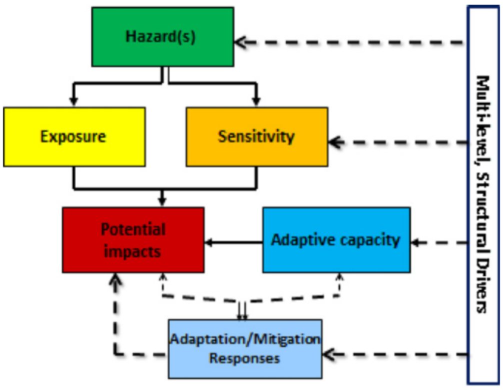


Figure 3 A conceptual framework of urban vulnerability to global climate and environmental change.

Source: Romero-Lankao et al. (2012)

Compared to the more general vulnerability concept depicted in Figure 1, this framework breaks down the vulnerability components further. It distinguishes between the hazard component and exposure component while in the previous version both components are merged. Following this concept, heat wave or other perturbation is recognized as the hazard element only. The effect of heat wave to exposure and sensitivity component will result in potential impacts. Meanwhile, adaptive capacity determines to what extend the urban system can cope with the impacts. Adaptation / mitigation provides means to help reducing the adverse impacts that rise. These components are influenced from external, multilevel and structural drivers. All in all, this framework recognizes the adverse impacts of climate change (e.g. heat wave) as hazard element (similar in disaster management). This way it corresponds with the vulnerability framework in SREX document (IPCC, 2012) as depicted in Figure 2. All in all, the framework by Romero-Lankao et al. (2012) is able to provide a satisfactory overview regarding heat wave issues with vulnerability concept. Therefore, their framework is used as basic framework for further discussion in this study.

2.1.3. Urban Heat Vulnerability Determinants

The heat vulnerability can be determined by numbers of variables derived from various sources (i.e. previous research, literature review and expert consultation) (Bao et al., 2015). There are numerous studies that have developed indicators for heat-related assessment. For instance, study by Stafoggia et al. (2006) regarding vulnerability to heat-related mortality showed that the elderly, women, widows and widowers, those with selected medical conditions, and those staying in nursing homes and healthcare facilities are vulnerable to high summer temperatures. Next, Johnson & Wilson (2009) investigate the relation of heat related death with distribution of vulnerable population comprises ethnicity, race, poverty, education in Philadelphia, USA. This study shows that there is a connection between poor communities with heat related death. Moreover, Loughnan, Nicholls, and Tapper (2012) developed an index of urban population vulnerability to heat stress. They identified "aged care facilities, nursing homes, Ethnicity, single person households, urban density, socio economic status, age, measure of disability, UHI, burden of disease, population density" (Loughnan et al., 2012) as the key factors of urban population heat vulnerability. On the following year, Aubrecht and Özceylan (2013) identified heat risk patterns in the U.S. National Capital Region by integrating heat stress and related vulnerability comprises of age, poor people, social isolation, education, land cover characteristic and linguistic isolation. Build upon meta-analysis study, Romero-Lankao et al. (2012) reveal that there are 13 variables commonly used to examine vulnerability to temperature-related hazard: hazard magnitude (i.e., temperature level), population density, age, income, gender, pre-existing medical conditions, minority status, education, poverty, acclimatization, and access to home amenities such as air conditioning and swimming pools. The summary of these heat vulnerability determinants from various literature can be seen in Table 1.

Table 1 Identified Heat Vulnerability Determinants

Determinants	Source
elderly, women, widows and widowers, those with selected medical conditions, and those staying in nursing homes and healthcare facilities	Stafoggia et al. (2006)
ethnicity, race, poverty, education	Johnson & Wilson (2009)
aged care facilities, nursing homes, Ethnicity, single person households, urban density, socio economic status, age, measure of disability, UHI, burden of disease, population density	Loughnan, et al. (2012)
age, poor people, social isolation, education, land cover characteristic, linguistic isolation	Aubrecht and Özceylan (2013)
hazard magnitude (i.e., temperature level), population density, age, gender, pre-existing medical conditions, education, income, poverty, minority status, acclimatization, and access to home amenities such as air conditioning and swimming pools	Romero-Lankao et al. (2012)

Source: synthesize of various sources

Following Romero-Lankao et al. (2012) framework (Figure 3) the identified heat vulnerability determinants can be generalized and attributed into urban vulnerability framework components ().

Table 2).

Table 2 Heat Vulnerability Determinants within Climate Change Vulnerability Framework

Components	Variable
Hazard	Hazard magnitude (i.e. heat wave)

Exposure	Population density
Sensitivity	age (infants, young population, elderly), gender, medical conditions (pre-and current), poverty, ethnicity, race, socio economic status, disability, aged care facilities, isolation (social, language, living alone).
Adaptive Capacity	Capital (education, income), acclimatization, and access to resource (health care, swimming pool, air conditioner, etc.)

Source: Derived from Romero-Lankao et al. (2012) combined with Table 1.

2.2. Usage of Demographic Data in Heat Urban Vulnerability Assessment

Having interest on the demographic change within future heat related urban vulnerability assessment, it is essential to investigating what are the common methods used in assessing vulnerability as well as identifying which kind of demographic data used for that purpose. Thus, the following section address this concern further.

2.2.1. Vulnerability Assessment Method

Common practice of assessing vulnerability is done by quantifying multidimensional concerns using indicators as proxies and later combined into a composite index allowing diverse variables to be integrated. Hahn et al., (2009) has coined 4 approaches of indices that are usually used in vulnerability assessment. The first method is averaging and additive approaches. In this method, the values of the indicators are normalized to an ordinal data scale. The second approach is Principal Component Analysis (PCA). In this method, the indicators are grouped based on the statistical relationships among the indicators according to similarity in their spatial distributions. The third approach is cluster analysis. In this method, the value of each indicator is aggregated and analysed based on the clusters that have been set prior to the data aggregation. The last approach is called Geons. Geons refers to an "aggregation method for modelling spatial units where similar (homogeneous) conditions apply with respect to a set of previously defined sub-indicators as well as spatial heterogeneity" (de Sherbinin, 2014, pg. 22). To add, the indices are calculated following certain unit of analysis (from global to community level) and then the result is mapped. In this sense, vulnerability assessment also refers to vulnerability mapping. By doing this, the location of areas with higher vulnerability or the concentration of vulnerable people can be detected easily and mostly it is done in Geographic Information System (GIS) environment.

In addition, assessing urban vulnerability requires analysis with appropriate spatial resolution. In this case, within-city analysis of heat vulnerability is required to give deeper information about local vulnerability than a national map (Reid et al., 2009). In relation with heat stress issue, data and information for heat vulnerability at spatial resolutions finer than the regional or city scale is fundamental to assist decision makers with the allocation of resources to cope with extreme heat events (Wolf & McGregor, 2013). Both concern makes understanding about intra-urban vulnerability is vital to deliver more accurate and specific adaptation strategies. This mostly done by using district, census tract, census block, district, or wards as the unit of analysis. Thus typical intra-urban vulnerability mapping within urban area is conducted in district level (Wolf et al., 2011), census block (Bradford et al., n.d.), census tract (Wolf & Mcgregor, 2013; Chow et al., 2012; Johnson et al., 2012) and District level (Harlan et al., 2006; Uejio et al., 2011). Nevertheless, conducting VA should seek to map at a resolution appropriate for the end users (decision makers) and should avoid using coarse-resolution data when higher-resolution alternatives are available, thus 30-250 meter resolution is desirable for VA in local setting (de Sherbinin, 2014b). Study of heat vulnerability assessment with fine resolution (100 m resolution) can be seen in the work of Morabito et al. (2015).

Vulnerability cannot be measured directly, therefore it involves a process of identifying "indicating variables," which point to the construct of vulnerability, and aggregating them (Hinkel, 2011). This indicating variables mostly derived from socioeconomic data such as economic, health and particularly demography.

2.2.2. Definition of Demography

Hauser and Duncan (1959) explain demography as "the study of the size, territorial distribution, and composition of population, changes therein, and the components of such changes". Following this definition, demography comprises dimensions of size, distribution, composition and changes (including the drivers). In regards to demography definition, "size" could refer to the magnitude of the population that could include number of population or population density; "distribution" refers to the spread of the population within certain area; "composition" refers to the structure of the population commonly described by age group, gender, ethnicity or race; and "components of such changes" mostly refers to the factors that influence the internal changes of population such as birth, death and migration. Given these points, it can be concluded that demography (represented by demographic data) describes the characteristics of population in regards to numbers, density, age and sex/gender of population whereas the changes of demography are influenced by birth, death and migration.

2.2.3. Demographic Data on Heat Urban Vulnerability Assessment

Demographic data is often used as one of the proxies in measuring the human vulnerability to heat wave (Aubrecht & Özceylan, 2013b; Johnson & Wilson, 2009; Romero-Lankao et al., 2012; Stafoggia et al., 2006). Reflecting the definition of demography in section 2.2.2 with the elaboration of urban heat vulnerability determinants in).

Table 2, there are few determinants sourced from demographic data:

- *Age*

Mortality risk varies with several social factors such as age in particular (Kovats & Hajat, 2008). Age can affect how efficiently an individual's body can adapt to inclement weather and maintain normal thermoregulatory processes (Bao et al., 2015). The elderly's adjustment ability is relatively poor, and they usually have chronic illness (Schwartz, 2005) and a higher probability of social isolation. Therefore, old age increases the risk of adverse effects in the face of extreme heat (Ebi, Teisberg, Kalkstein, Robinson, & Weiher, 2004). The old age here refers to the age more than 65 years old. On the other hand, young population (mostly under 5 years old including infant) also poses greater susceptibility to the effects of heat (Xu et al., 2014). Among of the reasons are: young population have less developed thermoregulatory systems and a greater body surface area-to-mass ratio compared to adults, allowing more heat and cold exposure (Blum et al., 1998); and they are dependent to others to protect from unsafe environment (Danks at al., 1962). As implication of the old and young age population, areas with high proportion of elderly and very young citizens are considered more vulnerable (Loughnan et al., 2012). Many studies have also used number of elderly population as variables in assessing heat vulnerability (i.e. Morabito et al., (2015), Inostroza et al. (2016)). Accordingly, the percentage of children and elderly in the population is one of the key aspects of the system's sensitivity to various climate change events (Kumar, Geneletti, & Nagendra, 2016). All in all, the high proportion of elderly (>65 years old) and young population (<5 years old) will make certain area more sensitive to heat wave.

- *Gender*

Moreover, gender was among the factors that increases individual vulnerability to heat wave as observed by a D'Ippoliti et al. (2010), they found that females are more susceptible to heat stress. Moreover, heat effects are greater as age increases, and greater in females than in males (Ishigami et al., 2008). Many studies have found that women pose higher risk for mortality to heat stress than men (Medina-Ramón et al., 2006; Michelozzi et al., 2006). This sense, similar with old and young population, the existence of women could make certain area more sensitive to heat stress. Therefore, to represent gender determinant, the proportion of female population is the data commonly used as indicator (Johnson et al., 2012)

- *Population Density*

Population density falls into exposure element because it describes how many people in certain area that are exposed to the heat stress. A previous study of 50 US cities found that larger heat effects is associated with higher population density (Medina-Ramón & Schwartz, 2007). Study by Kovats and Hajat (2008) reported that increased population density could also lead to increased heat risk. In vulnerability assessment practice, this determinant is represented with the number of people per certain extent of area (Johnson et al., 2009). To add, in regards to the spatial element possessed by this determinant, population density also shows used as proxy to identify the area where the population is exposed to the heat wave. Therefore, the population density is commonly attributed to the exposure component of CC vulnerability concept as it indicates the area of exposure to climate change impact.

- *Ethnicity and Race*

Study by Romero-Lankao et al. (2012) found that there is a relation between minority status with heat-related death. This minority status is commonly associated with ethnicity or race. The minority status is also associated with isolation in the sense of Aubrecht and Özceylan (2013) because of the language and culture barrier possessed by different ethnicities. Regarding future vulnerability assessment, the minority determinant is commonly represented by the population number of various races (i.e black, asian, etc) or ethnicity (i.e Hispanic, Indian, etc) (Bassil et al., 2010; Loughnan et al., 2012; Reid et al., 2009).

All in all, there is a linkage that can be drawn between demographic data, heat vulnerability determinant and urban vulnerability framework. This linkage is illustrated in the Figure 3.

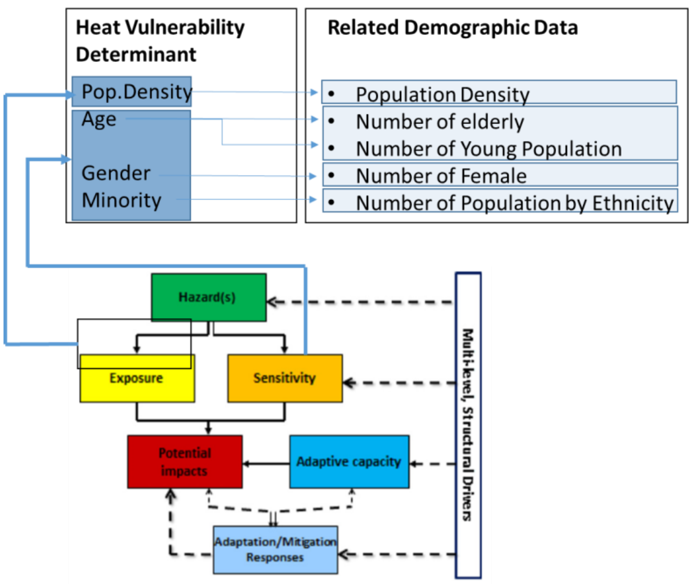


Figure 4 Relations Between Demographic Data, Heat Vulnerability Determinant and Urban Vulnerability

Source: Romero-Lankao et al. (2012), modified.

2.3. Conceptual Approach on Incorporating Demographic Changes into Future Urban Vulnerability Assessment to Heat Stress

To give an overview regarding future vulnerability assessment framework, this study reviewed the future vulnerability assessment practice conducted by GIZ & CCA RAI (2014). In their report, there are 4 steps of assessing future vulnerability (GIZ & CCA RAI, 2014): 1) assessing the future exposure, 2) assessing future sensitivity, 3) assessing future adaptive capacity and 4) assessing the overall future vulnerability. First, assessing future exposure refers to projection of the climate/hazard. Second, assessing future sensitivity refers to knowing how the projected climate would impact the system under influence in the future. Next, assessing future adaptive capacity relates more to the socioeconomic changes that are most likely to emerge in the system of interest in the future. Lastly, the result of these steps then combined into overall future vulnerability. The illustration of these steps is presented in Figure 5.

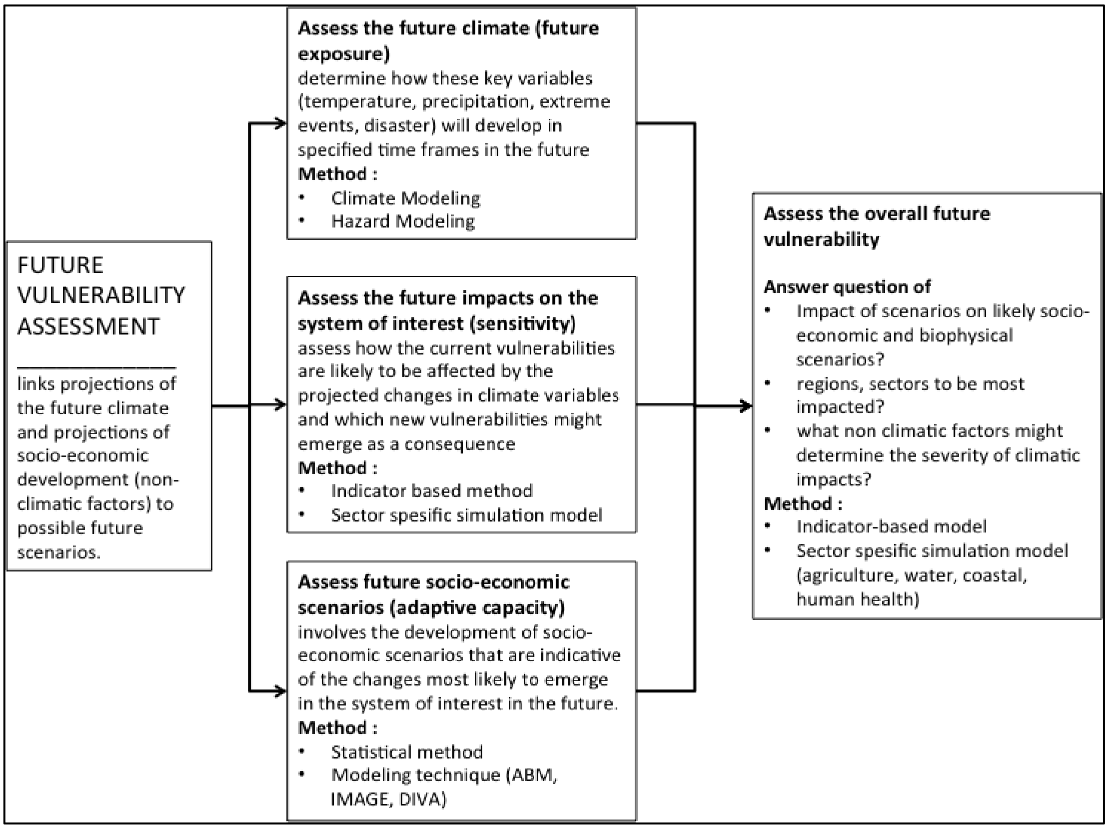


Figure 5 Future Vulnerability Framework by GIZ & CCA RAI (2014)

The main idea can be taken from GIZ & CCA RAI (2014) study is that future vulnerability assessment incorporates the possible states of the affected system in the future. It takes into account the long-term changes (spatially and temporally) in climatic and socio-economic variables in order to be able to increase the accuracy and efficiency of policy options and responses. (GIZ & CCA RAI, 2014). In regards to the way vulnerability is measured, the changes that might happen in terms of climate and non-climatic aspects should be able to be quantified. Therefore, the approach can be taken to conduct future vulnerability assessment or mapping is by projecting the data (climatic or non-climatic) that matters to determine vulnerability of a system to stress. This means that to incorporate demographic changes into future urban vulnerability to heat stress, one should use the projection of related data as input to measure vulnerability in the future. Build upon this understanding, this study proposes a framework that combined the future vulnerability assessment with the urban heat wave vulnerability concept (as depicted in Figure 4) into a so called "future heat related urban vulnerability assessment framework" (presented in Figure 6). This proposed framework serves as the guideline for further analysis.

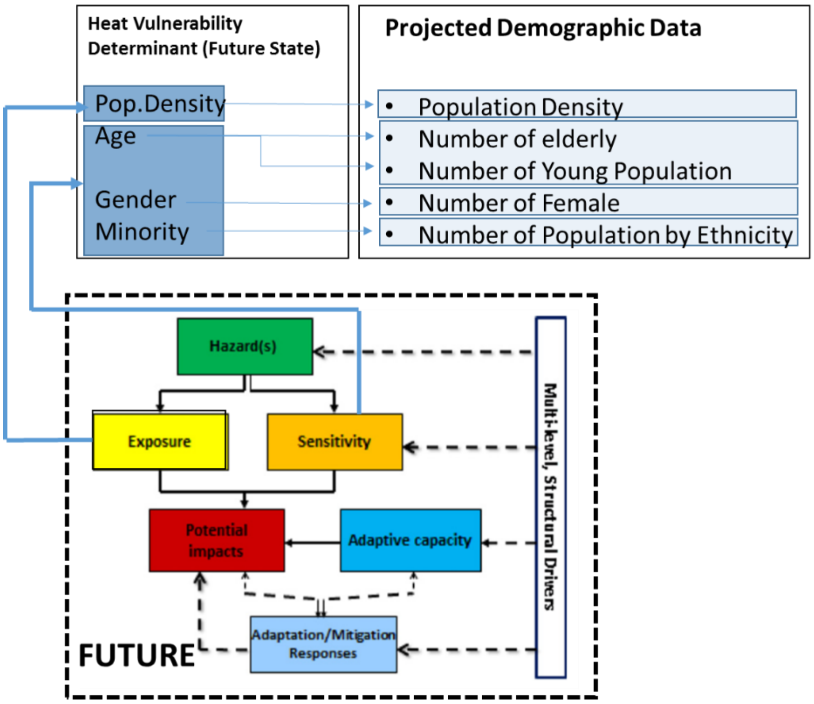


Figure 6 Proposed Future Heat Related Urban Vulnerability Framework
Source: Modified from Romero-Lankao et al. (2012)

2.4. Methodological Approach of Incorporating Demographic Changes into Future Urban Vulnerability Assessment to Heat Stress

The following parts discuss briefly about the concepts regarding the selection of vulnerability variables followed with the justification of the proposed methods. Next, this section will also explains briefly regarding basic concept of the proposed method.

2.4.1. Vulnerability Variables Selection and Proposed Method

It has been identified that there are numbers of urban heat vulnerability determinants coming from demographic data such as: age, population density, gender and race/ethnicity. This study serves as an exhibition of how the proposed methods could be beneficial in addressing the issue in future vulnerability assessment. Therefore, it is necessary to simplify the analysis process (considering the time limit and data resources also) as an example where later the same approach could be use in a more data intensive or further study. Given these points, the study focuses on the elderly (65+ years), young population (0 – 4 years), population density (hectare / meter), and female population as the measured variables for assessing future heat vulnerability due to their practical reason. These data are embedded in the basic population count data (census) which the projection of the population count are based on, thus the current and future data of these variables can be derived easily from the census and projection result with no additional data required.

Moreover, to project the selected demographic data, there are few ideas that can be explored. First, number of elderly, young population and female population, and population by ethnicity is associated with population composition which can be easily derived from the population count data. Thus, the projection of this data can be derived from the population count projection. In this sense, population projection could be the answer to get the future data of young, female, elderly and by ethnicity population. As an example, demonstration of this idea can be seen in study by Lutz & Muttarak (2017).

Second, as mentioned earlier, population density is represented with the number of people per certain extent of area (populated area). It can be calculated by simply dividing the number of population with the area limited by certain spatial extend such as administrative boundary (such as district, wards, census, block, etc). There are studies also that make use of land use/land cover (LU/LC) as the spatial boundary rather than the administrative boundary to calculate the population density by means of dasymetric mapping which produce population density data in high resolution (Gallego et al., 2011; Mennis, 2003, 2009; Peña, 2012). However, the change of population density is not only happening to the quantity of people overtime but also to the area where these people live. To capture these changes, generating population density with LU/LC is more relevant compared to administrative boundary. This mostly because administrative boundary is relatively constant but LU/LC is changing overtime as the consequences of the human activity. For this purpose, it is necessary also to capture the changes of LU/LC in that might occur in the future. Thus, LU/LC change modelling can be of useful for this matter. Given these points, land use/land cover change modelling coupled with population projection and dasymetric mapping model could be the answer to get the future population density data in high resolution. In addition, the fact that there is a spatial element changes embedded in the changes of population density makes this study not only try incorporate the change demographic data by quantity overtime but also the spatial changes (spatial-temporal change).

2.4.2. Population Projection

Demographer perceived population projection as a way to get insight of population in the future (Rayer, 2015). Technically, population projection could be defined as a numerical outcome of a set of assumptions in respect to the future population (George et al., 2004). The population projection could be conducted at global, regional or local scales. For local scale population projection, Smith, Tayman, & Swanson (2013) proposed four projection models: trend extrapolation, cohort-component method, structural and microsimulation method:

Trend extrapolation model determines the future population based upon the historical trend whereas the methods are ranging from a simple model (linear, geometric, and exponential growth) to complex model (polynomial, logistic curve fitting, and ARIMA time series) (Rayer, 2015). The main short coming of this model is that it does not take into consideration the element of population change (such as migration, death and birth,) so it fails to recognize the difference of demographic composition and cannot be related to the theory of population change. On the other hand, this model is easy to operate due to less data intensive and simple technical operability (George et al., 2004).

Cohort-component model is the most common population projection method used by many institutions throughout the globe. For instance, The US Census Bureau has consistently used this method to project population in the USA for decades (George et al., 2004). The major benefit of this method is that it could provide more detailed demographic information (e.g., age, gender, ethnicity) of population growth. The cohort-component model has been gradually extended to population projection of smaller areas (e.g., state, county) with availability of key demographic information. With the proper assumptions of three major components (births, deaths, migration) by age cohort, the model would produce the reasonable population projections at the smaller areas (Choi, 2010).

In a structural model, the population projection focuses more on the one or two population change element particularly on the migration (Rayer, 2015). There are two major types of structural models: economic-demographic and urban system models. Economic-demographic models project the future population based on complex economic theory complex, resource intensive, and the main usage is for large scale areas such as counties, metropolitan areas, states, and nations (Smith et al., 2013). The urban system models are more suitable for small scale projection; these models typically rely on GIS technology incorporating land use and transportation components (Rayer, 2015). Similar with the economic-demographic models, the urban systems models are data intensive and require substantial expertise technicality (Smith et al., 2013).

Microsimulation models work on the level of the individual or the household level rather than or aggregated data which rely on iterative random experiments (Imhoff & Post, 2008). Focusing on individual behaviour model, these models provide detailed projection outputs, and allow for scenario testing whereas on the downside, the models are data intensive and complex with issues on validation and assumptions underlying the model (Birkin & Clarke, 2011; Wilson, 2011).

Current usage of population projection in climate change domain mostly focused on investigating the relation between the climate and the adverse impacts on society. For instance, using cohort- component method, Petkova et al. (2016) projected the urban heat mortality by linking multiple population projection scenario, climate condition and adaptation pattern. In addition, climate change studies that utilized population projection mostly focusing on the overall future population number on the broad scale (national or regional) (e.g. Aubrecht et al., 2013; Huang et al., 2011; KC & Lutz, 2014; Petkova et al., 2016) and rarely focusing on demographic component the projection in local area.

2.4.3. Land Use Change Modelling

Land use change (LUC) is a dynamic and complex process, connecting natural and human systems (Koomen, et al., 2007). Land use change modelling can be described as "the art of expressing in mathematical terms the interaction of people and activities in the urban environment " (Prastacos et al., 2011 pg. 5). by expressing various relationships through mathematical terms, land use change modelling provides a framework for simulating future growth of cities while simultaneously estimating the impact of various policies (Prastacos et al., 2011). This way, modelling land-use change could help to understand urbanisation process which of value in informing policymakers of possible future conditions (Koomen, et al., 2007). Thus, land-use change models is beneficial as tools to support the analysis of the causes and consequences of land-use change (Verburg et al., 2004).

There are few technical terms that are important to be reviewed in regards to land use change model. First, one of the most important distinctions is about static and dynamic models. "Static (or cross-sectional) models directly calculate the situation at a given point in time, whereas dynamic models work with intermediate time-steps, each of which might become the starting-point for calculating the subsequent situation" (Koomen et al., 2007 pg. 3). The main difference of these two type of simulation is that the dynamic model results in a richer behaviour that could mimic better the actual spatial development meanwhile the static model gives a more aggregated and less precise result. Next, approaches the land-use change model may be either deterministic or probabilistic. Deterministic model reflects the cause-effect relations, whereas the probabilistic model considers the probability of land-use changes taking place by incorporating uncertainty element (Koomen et al., 2007). Lastly, the land-use change models can also be characterised by transformation or allocation type. Transformation models simulate the possible conversion into another land-use type, e.g. based on a transformation probability or the status of surrounding locations meanwhile allocation models, allocate a certain type of land use to a certain location that suit with its characteristic (Koomen et al., 2007).

Furthermore, there are various types of models that have been developed to model LC/LU. Referring to the review of practices and methods for land use change model by Verburg et al. (2004), there are four common methods of land use change model that can be identified:

- Starting from the micro level, models based on the micro-level point of view are all pointing on individual's behaviour simulation and relates it to changes in the land use pattern. Examples of this type of model are multi-agent model and economic land use model. Multi-agent models simulate decision-making by individual agents of land use change explicitly addressing interactions among individuals. Agent Based Model is the example of multi-agent based model implementation that has been used in various studies to model land use change (i.e. Cantergiani & Delgado, 2016; Ding, et al., 2015; Valbuena et al., 2010).
- Economic land use change models is a type of LU/LC change model that is built upon economic theory from the perspective of individuals who make land use decisions aiming to maximise revenue or utility of the owned land (Ruben et al., 1998). Study by Irwin & Geoghegan (2001) exhibits the usage of economic model in spatially explicit projecting land use change in Maryland, USA.
- Third type is cellular automata based LU/LC model. Cellular Automata is commonly used in urban studies especially regarding urban development. "Cellular automata can be thought of as very simple dynamic spatial systems in which the state of each cell in an array depends on the previous state of the cells within a district of the cell, according to a set of state transition rules" (White et al., 2001). Cellular automata are also seen as a paradigm to investigate complex spatial-temporal phenomena and to experiment for testing ideas (Itami, 1994). CA have become useful as a tool for modelling urban spatial dynamics and encouraging results have been documented in many studies (Batty & Xie, 1997; Deadman et al., 1993; White et al., 1997). CA-based models are simple and allow for dynamic spatial simulation (Torrens & O'Sullivan, 2001).
- Lastly, there is a group of models that are commonly referred to the integrated assessment models that attempts to capture the social, economic, environmental and institutional dimensions of a problem (Rotmans & van Asselt, 2001). For integrated assessment model type, the same conclusions applied: many models consist of linked subsystems that are not fully integrated. This means that these models are complicated but not complex, because of which their dynamic behaviour is almost linear and does not adequately reflect real world dynamics (Rotmans & van Asselt, 2001).

Many scholars have tried to utilized land use/land cover projection to address climate change issue. White et al. (2001) utilized CA model coupled with economic model to investigate the impact of climate change in St. Lucia. Solecki and Oliveri (2004) downscaled the climate scenario into land use/land cover by developing SLEUTH model that could accommodate the narrative derived from the climate change scenarios. (Zhang, 2016) investigated the influence of urban expansion to UHI effect by using statistical land conversion model in Beijing-Tianjin-Hebei metropolitan area. Similar effort was also done by (Lemonsu et al., 2015). They utilized the socio-economic land-use transport interaction model (NEDUM-2D), which is an example of integrated model, to investigate the effect of urban expansion to UHI and heat wave in Paris, France.

2.4.4. Dasymetric Mapping

Dasymetric mapping is a common tool used to disaggregate population data spatially into smaller unit of analysis. The data used mostly from census data ranging from administrative boundary (national, country, province, city, district, district) which is then converted into pixel based and seamless area such as land use or land cover. Dasymetric mapping can be defined as an area interpolation method that uses ancillary (additional and related) data to aid in the areal interpolation process (Mennis, 2003). Eicher & Brewer, (2001) have identified three traditional dasymetric mapping techniques: binary, three-class, and limiting variable. In binary technique area-class map delineating inhabited and uninhabited regions is used to redistribute data from choropleth map zones. Three-class approach the functional relationship between the area-class map categories and the statistical surface is quantified on a percentage basis. Meanwhile area-class map assigns maximum density limits to the area-class map categories. There is an effort to enhance dasymetric mapping technique by incorporating statistical technique such as regression (Reibel & Agrawal, 2007) as well as using multi-layer and multi-class data (Su et al., 2010).

In practice, dasymetric mapping tool is used for many purposes. For instance, Peña (2012) utilized dasymetric mapping to investigate urban growth of the lower Rio Grande Valley, Texas. The approach that was taken for the study was to use land-cover classification maps derived from satellite data to redistribute population to high, medium, and low density classes using a multi-class weighted distribution technique. Meanwhile, Tenerelli et al. (2015) utilized dasymetric mapping to develop population distribution model to support disaster risk management. (Nelson et al., 2015). In climate change studies, dasymetric mapping has also been used by many scholars. As examples, Aubrecht et al. (2013) used dasymetric mapping to determine long term impact variation of social vulnerability particularly to elderly. Next, Aubrecht & Özceylan (2013b) also utilized dasymetric mapping to investigate heat risk pattern in the U.S. national capital region.

2.5. Summary

This chapter tries to tie the knot among demographic data, heat vulnerability determinant and future vulnerability assessment (Figure 6). It is identified that demographic data such as number of elderly (>65 years), young population (<5 years), number of female, population by race/ethnicity and population density are the common data used in assessing vulnerability to heat wave. Reflecting back to the urban vulnerability framework by Romero-Lankao et al. (2012), number of elderly, young population, population by race, and also female population fall into sensitivity component meanwhile population density falls into exposure component. The fact that the changes of these selected demographic data would occur not only
The changes in regards to value and spatial extent of this data are the information that should be considered when conducting future vulnerability assessment to heat stress in urban setting. Therefore, there are few methods proposed for this purpose:

- To project the future number of elderly (>65 years), young population (<5 years) and, population by race and number of female in the future, it is necessary to project the population based on age and sex and ethnicity future population numbers as it provides the base data to derived these desired urban heat vulnerability indicators. For this purpose, cohort-component model is considered as the suitable method due to its output which is based on age and gender and the flexibility of its calculation mechanism that can be operated for specific ethnic group/race individually.
- On the other hand, projecting future population density in fine resolution requires not only population projection but also a population disaggregation model combined with future land use/land cover. For this purpose, dasymetric mapping is considered as a convenient method to disaggregate population because of the easiness of operability which has been tested in many studies. Next, CA model is considered as the suitable method to be used in this study because the model can do efficient computation and allow analysis with very fine spatial resolution (Roger White, Uljee, & Engelen, 2012) is in accordance with the requirement of intra-urban heat vulnerability mapping. In addition, CA-Land use change model is relatively simpler to operate and can be done in any platform (preferably via ArcGIS) which favours the author in doing the modelling.

In addition, based on the discussion in the previous sections, it is identified that demographic change is affecting mostly to the exposure and sensitivity of urban area to the threat of heat wave. This way the demographic changes is not effecting the adaptive capacity due to the reason that the determinants and data used to measure adaptive capacity are not coming from the pure demographic data. The adaptive capacity to heat wave mostly attributed to the resource that can be used to cope with heat wave such as capital (education, income), acclimatization, and access to resource (health care, swimming pool, air conditioner, etc.). In this view, demographic change is not enough to capture the changes that might happen regarding these factors in the future. There are more analysis covering the subject of economic, social and infrastructure study required to address the changes that might affect the adaptive capacity in the future. Hence, the future changes of adaptive capacity are not of interest of this study.

3. RESEARCH SETTING

This chapter explains the setting of the research. The chapter starts with the description of the case study, explanation of the methodology applied in the study, and it ends with the description about the data set and data preparation.

3.1. Study Area

The following section explains the justification of the case study selection followed by brief explanation regarding its background, location characteristic, development pattern and land use change trend.

3.1.1. Case Study Selection

Cities in the USA are some of the cities affected by heat wave in the globe. For example, in the Summer 2011 American heat wave event, cities on the southern part of the country including Houston, Dallas, Austin, Oklahoma City, and Wichita, set records for the highest number of days recording temperatures of 100ºF or higher in those cities' recorded history (Melillo, et al. 2014). It is projected by mid-century (2041 – 2071 period), these cities will experience increased hot days and warm nights (Melillo, et al. 2014). Oklahoma City carries more the effect from the heat stroke because it is the most populated cities among those cities.

Oklahoma City possess an important function of Oklahoma State due to its function as the state's economic centre which mainly focused on oil and gas industry. This condition makes Oklahoma City an attractive place for people to come to get a better live. As the consequence, the city possesses a high population growth which is also accompanied by rapid physical development.

With high population growth, Oklahoma City will be more populated with more physical development in the future. The threat from heat wave possess by the city is aggravated with urban heat island (UHI) that could increase the temperature of the urbanized area by 0.5^{o} C during the day and 2° C warmer at night compared to the rural area. The heat wave and UHI impacts of the city is going to be worse in the future as it is predicted by scientists that the global warming and climate change impacts are becoming more severe (IPCC, 2013). The fact that the city possess high population growth and rapid physical development creates another problem as it could affect the city's vulnerability to heat wave in the future. Therefore, it is necessary to conduct studies to address climate change and heat waves issues in general in Oklahoma City. Given these points, Oklahoma City is considered as an appropriate case study to be used in this research.

3.1.2. Study Area Background

Oklahoma City is the capital city of Oklahoma State. In total, the city covers the area of 1,606.67 km^2 with urban area expanded through several counties such as Cleveland County, Canadian County and Pottawatomie County. In addition, there are 5 small cities that is not included in the administrative boundary of Oklahoma City, they are Mustang city, Bethany City, The Village City, Nichole Hills City, Valley Brook City and Forest Park City. These small cities are not of interest in the study and excluded for this study. The city is further divided into 8 wards (see **Error! Reference source not found.**) which are functioned as representative boundary for the election.

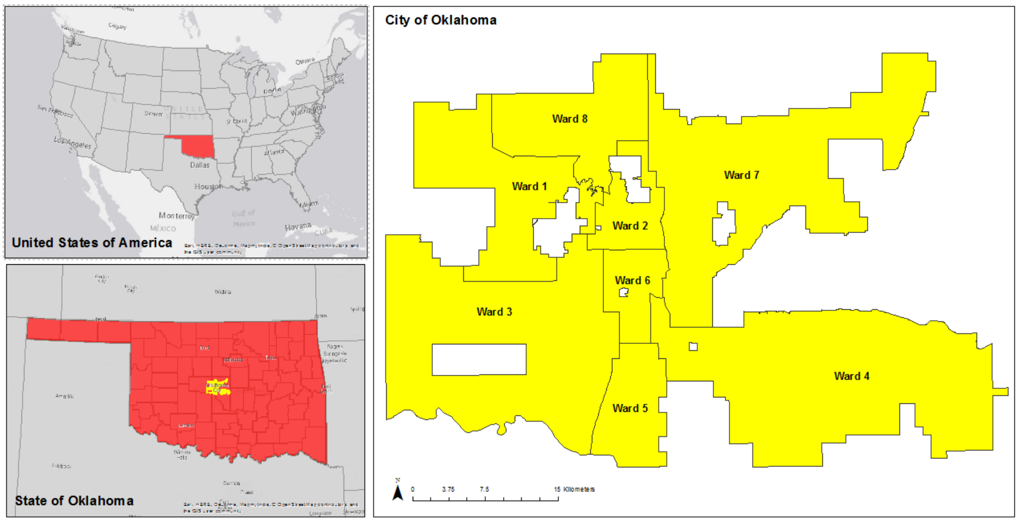


Figure 7 Case Study Area

The explanation of the study area background is divided into two parts; the city level and ward level. The city level gives explanation about the city's condition in general meanwhile the ward level explains the condition of the city in regards to the wards characteristics.

City level

As the Capital City, Oklahoma City is the most populated city in the State of Oklahoma. Based on 2000 census, there were 506,132 people resided in Oklahoma City with 7.3% of the population were in the age of 0-4 years and 11.5% of the population were in the age of 65 years or older. In the next decade, as enumerated in 2010 census data, the total population increased to 579,999. Within this year, 7.9% of the population are in the age of 0 – 4 years old, and 26.3 % of the population are over 65 years old. This data shows that there was a significant increase in the percentage of the elderly (+65 years old population) from 2000 to 2010. This data indicates that Oklahoma City was experiencing aging population in the last decade.

In the state level, Oklahoma State's economy is mainly influenced by energy industry such as oil and natural gas mining. This is reflected with 15.5% industry share based on GDP in 2016 together with government spending, which are the second largest portion after trade, utilities and transport sector (see Figure 8) (Oklahoma Department of Libraries, 2016).

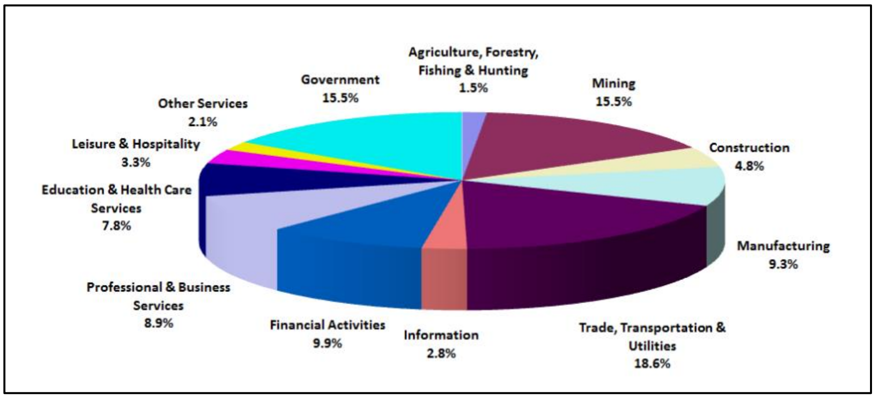


Figure 8 Industry Share of Oklahoma's Economy

Source: Oklahoma Department of Libraries (2016)

The dynamic of energy industry has influenced the migration in Oklahoma in the last decades (State Chamber of Oklahoma, 2014). This influence is mainly attributed to the job creation in energy industry that correlates with the world's natural gas and oil price. The evidence is shown by the population change in 2000 – 2010 period. Within this time frame, the price of natural gas and oil showed increasing trend and reached the all-time peak price. The high price trend favoured the energy industry so that many jobs were created within this industry. There were roughly 29.000 wage and salary jobs created by oil and gas firms in Oklahoma State in the same period (State Chamber of Oklahoma, 2014). In addition, it is reported also that the growth in oil and gas industry in Oklahoma has raised the per capita income (from 85% to 96%), boosted investments and gave positive impact in other economic activities (State Chamber of Oklahoma, 2014). These points made Oklahoma an attractive place for people who are looking for a better job. Thus, Oklahoma City as the biggest city mostly became the main destination of the people that came to Oklahoma State. This is showed by significant increase of the city's population with 14.9% increase between 2000 – 2010 (US census bureau) which is mainly attributed to the migration into the city (see Figure 9).

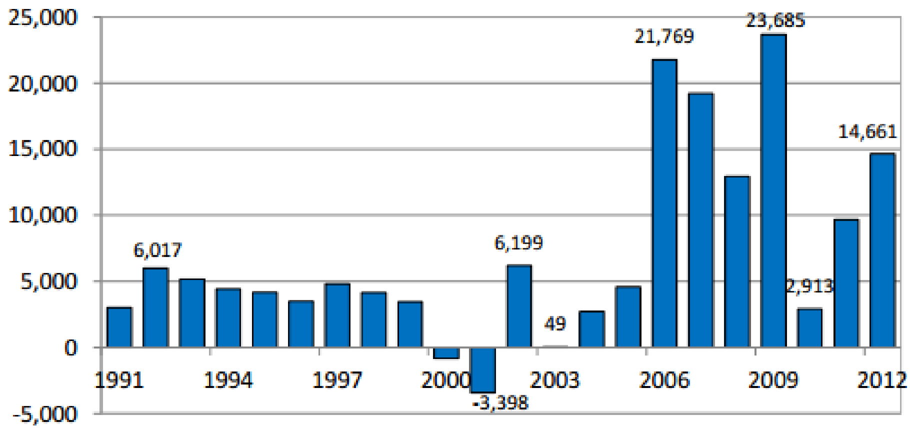


Figure 9 Oklahoma Population Net Migration in 1991 – 2012

Source : State Chamber of Oklahoma (2014)

It is expected that energy industry will continue giving impact for Oklahoma City in the future. As the price of oil and gas are still going to be fluctuated throughout the years, oil and natural gas mining would still be a significant jobs provider of the city. The city's population would still increase particularly with population in productive age that are looking for jobs. Most likely this condition would change the population composition of the city which is subject for further analysis in this study.

Ward level

The profile of these wards can be seen in Table 3. The table, the northwest ward is a ward with the highest population increase (up to 40%). Ward 2 and 6 are the downtown area of the city which is also the location of the old part of the city. The urbanized area of Oklahoma City mostly covers the area of ward 1, 8 , 2, 6 and 5 meanwhile ward 3, 7 and 4 are the area of urban-rural transition. Moreover, looking at the population composition, it can be see that ward 7 is the least populated by the white ethnicity. Next, ward 3 and 6 are where most of the elderly live. The young population is concentrated more in wards 1, 2 and 5 meanwhile ward 8 are the area where most of the women are concentrated.

Table 3 Wards Profile

Wards	Geographic Description	Population Increase 2000 – 2010 (%)	Typical Land Use	Population Composition in % (2010)			
				White ethnicity	Elderly (65+)	Young Population (0-4)	Women
1	Northwest Central	14	Settlement	76	7	13	52
2	North Central (downtown)	1	Commercial, Settlement	59	7	13	52
3	Southwest	18	Settlement	70	9	10	50
4	Southeast	14	Settlement, Agriculture	67	8	10	49
5	South Central	24	Settlement	76	7	13	48
6	Downtown	6	Commercial, industry, Settlement	51	9	8	47
7	Northeast	7	Settlement, Agriculture	38	8	12	52
8	Northwest	40	Settlement	79	7	12	53

3.1.3. Location Characteristic

Oklahoma City is located in a non-hilly area with the elevation ranging from 274 m above sea level in the eastern part of the city to 449 m above the sea level in the western part of the city. The city is crossed by the Canadian river and several streams which make the city is a flood prone area. In addition, there are three big lakes exist in the city boundary which are mainly functioned as tourism place.

Oklahoma City lies in a temperate humid subtropical climate with consistent winds coming from the south or south-southeast during the summer. This condition helps temper the hotter weather. Consistent northerly winds during the winter can intensify cold periods. Oklahoma City's normal annual mean temperature is 16.3 °C with precipitation of 928 mm averaged annually. Within a year, May until September are the hottest months with average temperature ranging from 22.4 °C – 15.3 °C (National Weather Service, 2016). The maximum temperature in the summer time reached 45 °C as experienced in August 2012 (National Weather Service, 2016).

3.1.4. Development Policy

Currently, Oklahoma City is following their long-term development plan called the Planokc (www.planokc.org). Planokc that was launched in 2015 is their first comprehensive plan since 1977. The planokc identifies ways to maximize Oklahoma City's strengths which goals are developing inclusive transportation system; increasing housing quality and quantity; building pro health and wellness urban environment; catalysing development and innovation; ensuring stable, safe, attractive, and vibrant neighbourhoods; sustainable and improved quality of life; and preserving rural area as well as natural resources. The planokc comprises of many plans in many dimensions. One of the plan is regarding the zoning regulation that is represented in the form of Land Use Typology Area (LUTA). There are two main typology land use areas: base land and layer land. Base typology areas define a spectrum of development intensities¸ comprised of open space, rural intensity, urban intensity and downtown usage. Layer typology areas describes the designation of the base LUTAs. This includes the area of agricultural preserve, urban reserve, employment reserve, industrial, regional, commercial and TOD district. Furthermore, this land use arrangement is detailed with the existence of the zoning area which is called the straight zoning. The straight zoning defines the usage of land in parcel level. This zoning area consists of 34 areas, arranging various type of parcel usage regarding settlement, industrial and commercial function. These LUTA and straight zoning area are the guidance that will lead the physical development of the city in the future.

3.1.5. Land Use Change Trend

To give an overview of the land use trend in Oklahoma City, the land use maps in 2000 and 2010 derived from the Landsat data was compared. The comparison revealed the land use changes over 2000 – 2010 period as presented in Table 4.

Table 4 Land Use Change of Oklahoma City in 2000 – 2010 period

Land Use	2000 (ha)	2010 (ha)	Difference (Ha)
Medium Density Urban Settlement	1706	2324	618
Low Density Urban Settlement	15300	22396	7096
Rural Settlement	1712	1503	-209
Commercial Area	10085	10868	783
Vacant Land	120680	112392	-8288

Point of observation is focused on the area difference of the urban settlement land use classes. It is observed that these land uses classes are increased within 2000 – 2010-time frame. It is also noticeable that between these land use classes, the low density urban settlement area is experiencing the most significant increased. Referring to the population increase within 2000 – 2010 period, it seems that the population increase contributes more to the increase of the low-density settlement area rather than the medium density settlement. In addition, judging from the land use maps in **Error! Reference source not found.**, the low density settlement is growing by following the edge-expansion pattern (Sun et al. 2013). In the city context, this finding implies that the city grows by outward expansion of low density settlement area located on fringe of the city. This growth trend is supported by the condition of the city which has unlimited supply of land (due to flat area) with low land values (Penticton, 2015).

In contrast, the data shows that the rural settlement area was decreased by 209 ha within 2000 – 2010 period. In the real condition, it is impossible for the rural area to decrease this much as there is no crucial event happened in 2000-2010 period that could cause this (such as war, or disaster). Most likely this is due to the error from the remote sensing process. It was found that visually, the rural settlement area is not visible within the 30-m resolution satellite imagery data so that the reflectance of this area is not well captured in the supervised classification process in both years. Consequently, the remote sensed image cannot detect the rural settlement area adequately for both 2000 and 2010 satellite imagery. Therefore, when both maps are overlaid, it gave fewer the rural settlement area.

3.2. Methodology

There are there steps employed in the research: identifying the future population composition (Chapter 4), estimating high resolution future population density (Chapter 5), and calculating current and future vulnerability index (Chapter 6).

The first phase was about identifying the future population composition. It started by projecting the future population count of Oklahoma City in ward level with 2030 as the target year. The population projection was conducted in ward level due to the reason that the interest of the study is to see the demographic changes within the city level. Meanwhile, year 2030 was selected as the study time horizon due to the consideration that 20 years' period is sufficient to capture the changes that might happen within the urban system and the projections post 2030 are too uncertain. Consequently, year 2030 was set as the timeline basis for the whole analysis. Furthermore, the population projection was conducted by using cohort-component method. This model was run by applying three migration scenarios, aimed to address the uncertainty in the future. Lastly, the future population composition was derived from the projected population numbers. Detail elaboration of this phase is presented in chapter 4.

The second phase of the research was to estimating high resolution future population density. It started with projection of the future land use of Oklahoma City by means of GIS-based CA model, aiming the same target year as the population projection. The land use projection was produced the configuration of the land use change model consists of land conversion probability calculation and followed by future land allocation. The land conversion probability was calculated by taking into consideration several development driving factors / such as environment, transportation infrastructure and land use that were selected based on literatures with also considering the city development context. The future land allocation determines the number of increased area which is derived from the population projection result. To address the uncertainty, this study employed two land use change scenarios which have different configuration setting. Combined with the population projection result, the outputs of the land use change model then used to derive high resolution population density by means of dasymetric mapping. Detail description about this phase is presented in chapter 5.

Lastly in the third phase, a composite vulnerability index was calculated. This chapter starts with calculation of all vulnerability variables and continues with the calculation of the vulnerability index. The vulnerability index does not include all the heat vulnerability components (as described in chapter 2) but rather focused merely on sensitivity and exposure component. This is due to the reason that this study tries to integrate socioeconomic scenarios and projections in future vulnerability assessment which is mainly attributed to the socioeconomic components of vulnerability (exposure and sensitivity). In this sense, it is useful to focus on these components rather than conducting full heat stress vulnerability assessment as it makes the analysis simpler and less data intensive. Next, the index was calculated for the current condition (2010) and the future condition (2030). The index score of both conditions then compared to see the effect of demographic changes in the future. The calculation method and result of this phase is reported in chapter 6.

In addition, interested in the future vulnerability condition in detail level within the city area, this study adopted high resolution heat wave vulnerability assessment demonstrated by Morabito et al. (2015). They conducted heat wave vulnerability assessment in 100-m grid spatial resolution. As implication, 100-m grid spatial resolution is applied as the unit of analysis in the land use modelling, calculation of vulnerability variables as well as the calculation of composite vulnerability index.

The whole phase of this research is described in a flow chart presented in Figure 10.

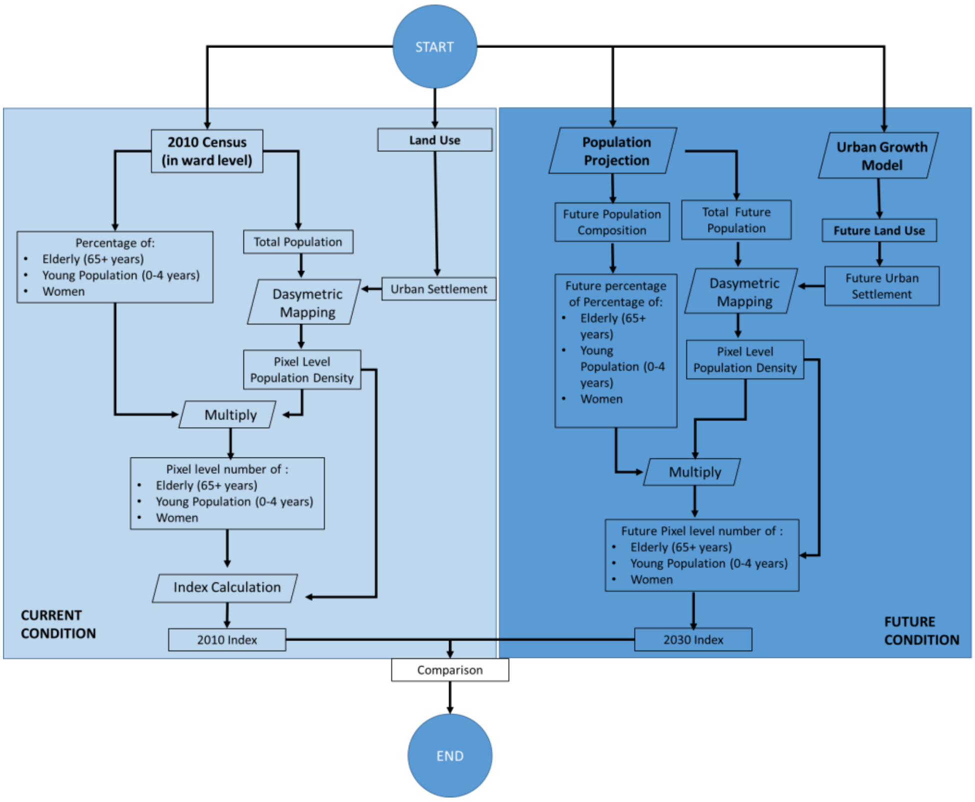


Figure 10 Research Flowchart

3.3. Data set and Data Preparation

The following sections explain the data set used in this study including the brief explanation of how these data area prepared to be used in the analysis.

3.3.1. Data Set

There are two major data set used in the research; statistical and spatial dataset. The statistical dataset consists of decennial census data of Oklahoma City in year 2000 and 2010 obtained from the US Census Bureau (https://www.census.gov/). These data mainly used to conduct the population projection in phase 1. On the other hand, the spatial dataset comprises of raster and vector file which are listed in Table 5. The spatial data set is used mainly to conduct the land use projection in phase 2.

Table 5 Spatial Dataset

Data	Format	Year	Source
Landsat Image 4-5 TM	Tiff file	2000,2010	USGS
LUTA	Jpeg file	2016	www.okc.go
City Boundary	GIS Shapefile	2016	www.okc.go
Wards Boundary	GIS Shapefile	2016	www.okc.go
Oklahoma City Census Tract Boundary	GIS Shapefile	2000,2010	US Census Bureau
Oklahoma Road Network	GIS Shapefile	2016	www.okc.go
Straight Zoning	GIS Shapefile	2016	www.okc.go
Oklahoma School Area	GIS Shapefile	2016	www.okc.go
Water Body	GIS Shapefile	2016	www.okc.go

3.3.2. Ward Level Data Generation

To capture the future vulnerability variation within the urban area, this study uses wards boundary as the unit of analysis for the population projection. Therefore, ward level population data is required to perform the projection. Unfortunately, the necessary data is available in census tract level in the form of excel table file. To overcome this issue, the census tract data was aggregated according to the wards boundary. The aggregation process was done in ArcGIS. First, the census tract polygons in 2000 and 2010 were grouped into the respective wards. Next, the census data (in excel file format) of both years is linked with the census tract polygons that have been group into ward boundary. The aggregated data for each ward is produced by summarizing the grouped census data according to the wards boundary.

3.3.3. Land Cover / Land Use Generation

Landsat 4-5 TM satellite imageries in July 2000 and July 2010 were used to derive the land cover of Oklahoma City. The satellite data of these years were used to match the base year (2000) and launch year (2010) of the population projection. The images were taken in the same month to help reduce the variation of vegetation reflectance and the effect of sun positions. The images in this month are also the best available during the analysis period in terms of image quality, concerning the clouds coverage and shadow. To avoid distortion, the images are projected into WGS 84 UTM Zone 14. Later, these images are clipped with the city boundary polygon obtained from the website of Oklahoma City municipality (data.okc.gov). To ease the land classification process, the water body is also eliminated from the images. This was done by subtracting the image with water body polygon that are also obtained from Oklahoma City municipality website. All this process was done with ERDAS IMAGINE 2015.

The next step is to classify the image into land cover. Using supervised classification feature in ERDAS IMAGINE 2015, a signature file that contains the sample reflectance of each land classes target was made. There are approximately 10 samples taken for each land cover classes. The “natural colour” band combination that comprises of band 3 (red), band 2 (blue), and band 1 (green) was used to take the sample. In this band combination, ground features appear in colours similar to their appearance to the human visual system. This process was conducted for both images, 2000 and 2010. Based on the visual comparison, there are three urban classes that can be distinguished: two urban classes (type 1 and type 2) and non-urban land cover class.

Furthermore, the result of the image classification is converted into land use. This was done by visually comparing the produced land cover with the land use typology area (LUTA) and straight zoning (mentioned in sub sub chapter 3.1.3). Prior to the land use conversion, the produced land cover data is resampled from 30 m resolution (original resolution of Landsat data) into 100-m resolution as the desired resolution of this study. There are 4 different land uses derived by overlaying the land cover with LUTA: rural settlement, urban settlement, other urban land usage (commercial, industry, offices, etc.) and vacant land (vegetation, bare ground, etc.). Furthermore, since the urban settlement is the main interest of the study, this result is overlaid again with the straight zoning area to provide a detail typology of the urban settlement. The straight zoning area comprises of many types of urban settlement usage. This usage can be group into two types: low density urban residential area and medium density urban residential area. The low residential area mostly comprises of single-family housing meanwhile the middle density residential area comprises of settlement with higher intensity such as multi-family housing. The final output of this step for both years (2000 and 2010) is a land use map with 5 classes: rural settlement, medium density urban settlement, low density urban settlement, other urban, and vacant land. This result mainly served as the basic data for study area description and to develop the LUC model.

4. IDENTIFICATION OF POPULATION COMPOSITION CHANGE IN THE FUTURE

This chapter elaborates the process of future population composition identification by means of the population projection. The chapter starts with explanation about the population projection method, population growth scenario, validation, calibration and the result.

4.1. Method

The population projection in this study was produced by means of cohort component method. The projection was calculated in 5-years' increment from year 2010 into 2030. This method comprises of three population change components: birth, death and migration. The process started with calculating the number of birth which was done by multiplying the birth rate within each age cohort with the number of female population of that age group. Unfortunately, there is no birth rate data available for Oklahoma City. Therefore, the average birth rate of Oklahoma State from 2000 – 2010 obtained from Oklahoma State Department of health (http://www.health.state.ok.us/ok2share/) is used to substitute the birth rate of Oklahoma City (see Appendix A). Mathematically, the number of future birth in the next 5 years calculated by the formula of:

$$\mathbf{Birth_{t+5} = female\ population_{\,t} * (birth\ rate) * n}$$

With "$Birth_{t+5}$" as the birth at the year t+5, "t" as the base year, and "female $population_t$" as the female population at the base year. This calculation was not applied to all age groups, but only for the fertile age (14 – 44 years old). The number of baby born resulted from the fertile age then summed to get the total amount of baby born in the next 5 years. Next, the total amount of birth was multiplied by 0.52 to get the number of male babies (attributed to male population in 0-4 age cohort) and 0.48 to get the number of female babies (attributed to female population in 0-4 age cohort).

Next step is to calculate the number of the people that are survived in the next five years. This was done by multiplying the 5-years survival rate with the total population in each age cohort. The survival rate for 5-year projection was calculated by using the formula of:

$$\mathbf{5\text{-}years\ survival\ rate = (1\text{-}Mortality\ rate/1000)^5}$$

Similar with the birth rate case, the mortality rate for Oklahoma City is replaced with the average mortality rate of Oklahoma State from 2000 – 2010 obtained from Oklahoma State Department of health (http://www.health.state.ok.us/ok2share/) (see Appendix B). The result of this calculation represents the number of people that are still alive in each age cohort in the next 5 years. For instance, using 2010 as the launch year and 2015 as the target year, the number of population in the age group of 5-9 years in 2015 is obtained by multiplying the number of population of 0-4 years in 2010 with the 5-years survival rate.

The last step is calculating the migration component. In this study, the population projection is calculated in ward level. Thus, there is no data available regarding the movement of people in and out of each ward. Given this condition, the migration data for each age cohort in each ward is calculated by subtracting the number of population from official census in one year (2010 census) with the population from previous census (2000 census), together with the natural population increase (mortality and fertility only) within the two census years. This method is well known as residual method and mathematically described as:

$$\textbf{Net migration} = (\textbf{population}_{2010} - \textbf{population}_{2011}) - (\textbf{births} - \textbf{deaths})$$

With, "population_{2010}" as the number of population in the launch year (2010 census), and "population_{2000}" as previous census (year 2000).

The result of this calculation is the net migration which reflects 10-year migration trend of each age cohort within each ward. This calculated migration number then divided by two to get the 5-year migration. The value resulted from this calculation is added every 5 years in the projection process starting from the 2015 projection until the projection reached the target year (2030).

Combining all the population change components, the projected population that includes births, survival population and migration for each age cohort in each ward for the next 5 years is calculated as:

$$\textbf{Population}_{t+5} = (\textbf{population}_{t} \textbf{ x 5-years survival rate}) + \textbf{Birtht}_{+5} + \textbf{Net migration}$$

With, "population_{t+5}" is the population in the next 5 years, "population_{t}" is the population in the launch year, "Birth_{t+5}" is the number of birth in the next 5 years, meanwhile *Net migration* is the migration number that is added when calculating the population in every 10 years from the base year and applied for both scenarios.

4.2. Population Projection Scenarios

In addition, to address the uncertainty of population change in future migration scenarios were employed in the population projection. As mentioned in the background part, Oklahoma City population growth is influenced by the jobs coming from oil and gas industry which are sensitive to global oil and gas price. Considering the dynamic of the oil and gas price, there are three migration scenarios employed to project the future number of population in Oklahoma City (see Table 6).

Table 6 Population Projection Scenario

Population Projection Scenario (PPS)	Assumption
PPS 1	Migration number is constant
PPS 2	Migration number is reduced by 10% every 5 years
PPS 3	Migration number is increased by 10% every 5 years

PPS 1 is a baseline scenario (current trend) whereas the mortality rate, birth rate and migration number are held constant over the population projection horizon. This scenario assumed that the population growth trend in 2000 – 2010 period continues in the next decades. Next, in PPS 2, the migration number is reduced by 10% every 5 years while mortality and birth are held constant over the projection period. This scenario is employed to address the possibility the effect of the current oil and gas price which stand at a lower level compared to 2000-2010 price. The falling oil and gas price could affect the job market in the city which lead to less job creation in the next decades and as the consequences, the migration numbers might fall. In PPS 3, it is assumed that the migration will be increased by 10% every 5 years while mortality and birth rate are held constant. This scenario is employed to address the possibility of rising oil and gas price considering the current US policy which favours the fossil fuel industry. Rising oil and gas price might induced more job creation and respectively, more job creation that could lead to increased migration in the future. Furthermore, PPS 2 and PPS 3 were applied for year 2020, 2025 and 2030 projection. Projection for year 2015 was excluded because the year itself has passed. Therefore, it is make sense to apply the scenario for the next projection year. In addition, the 10% migration difference in both scenario was derived from the population growth difference when the oil price started rising between 1990-2000 and 2000-2010 period. In this sense, the 10% value reflects the effect of high oil and gas price to the migration. This value is considered realistic as it reflects the real migration change during the oil and gas price boom.

4.3. Validation and Calibration

After using the conventional cohort-component method to produce series of population projections, the next process is to validate the result with the actual population of Oklahoma City. Scenario 1 was used to validate the population projection result due to the reason that this scenario reflects the current trend (business as usual) without modification of the population change component. In this sense, Scenario 1 is considered as the projection trajectory that is more realistic to happen in the future.

The validation started by aggregating the population number projection of scenario 1 in the city level for the year 2015. This data the then compared with the Oklahoma City population estimation in 2015 obtained from US Census Bureau. The result for 2015 was 618.202 people meanwhile the population estimation was 631.346 people. The projection underestimated the population in 2015 as much as 13.144 people or approximately 2%. To get a better result, the model then was calibrated by applying the following ratio (R) as an adjustment factor to the future population projections:

$$\mathbf{R = Estimated\ Population\ 2015\ /\ Projected\ Population\ 2015}$$

The ratio generated from this calculation was 1.0213 and this ratio was multiplied to each cohort, sex, ward in all the population projection scenario to get a calibrated result.

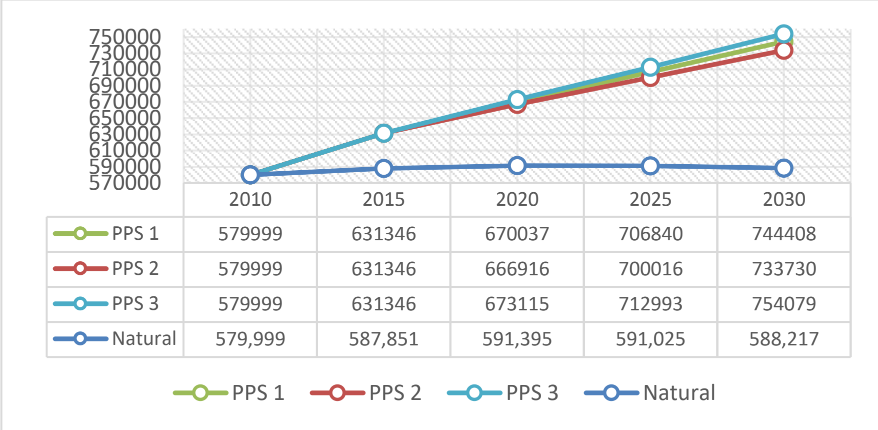
4.4. Result and Discussion

The result and discussion presented in this chapter is divided into two parts, the city level and ward level. The city level part shows the result in regards to the whole city context meanwhile the ward level part elaborates the projected population of each projection type in respect to the ward division within the city.

4.4.1. City Level

The final calibrated and aggregated result for every population projection type including the natural increase of the city (projection without migration) in city level is presented in Figure 11. The graph shows increased population for the next 20 years in all population projection scenarios. If the current population growth continues (PPS 1), the population will increase by 28% with total projected population of 744.408 people. Compared to the real condition in 2010 census with 579.999 population, Scenario 3 yields in the highest future population number in 2030 with 754.079 people (30%). Meanwhile, PPS 2 yields a lower population number with 733.730 people (27%). Looking at this data, the applied migration scenarios are affecting the population growth with 1 – 2 % difference with the current population growth trend of the city. However, the decreased and increased migration scenario gives different numbers of future population but both shows that the population in Oklahoma City will be increased in the next 20 years. As implication, this could mean that with the effect of the oil and gas price dynamic to the city population growth, Oklahoma City's population could grow by 27 – 30% in 2030.

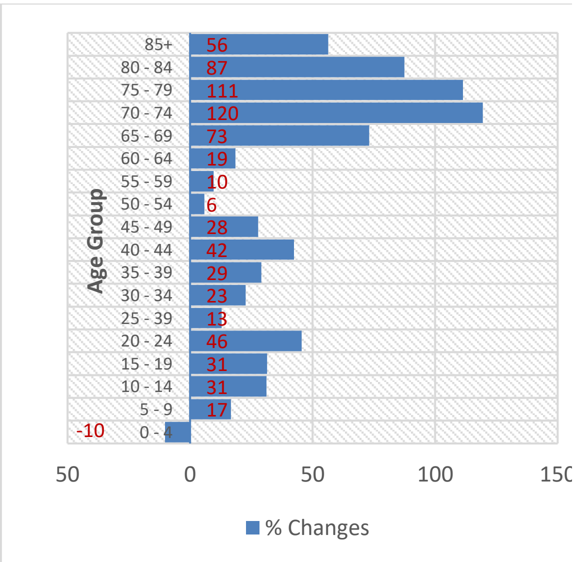
Looking at the bigger context, in the state level, it is projected that the population will increase by 14% or approximately equal to total 4,302,501 people (Barker, 2012). Comparing the percentage of population increase between the state and city level, Oklahoma City clearly shows higher population increased (in all scenarios) in 2030. Possible explanation is that because the migrants that are coming to Oklahoma State is concentrated in Oklahoma City due to the attractiveness of the city. Therefore, Oklahoma City is expected to experience higher population growth compared to the state level.



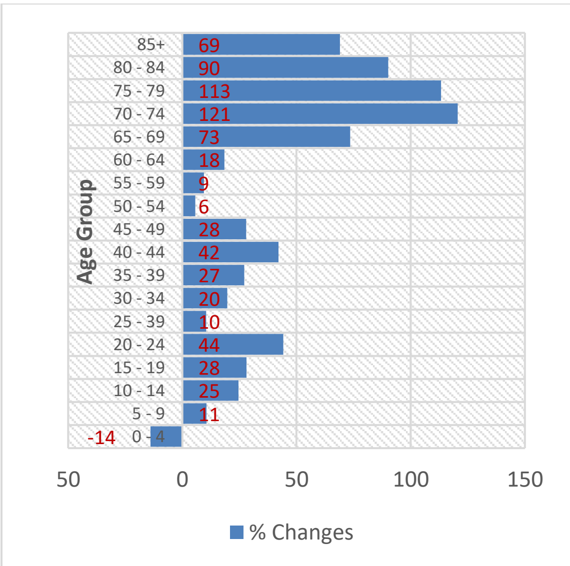
	2010	2015	2020	2025	2030
PPS 1	579999	631346	670037	706840	744408
PPS 2	579999	631346	666916	700016	733730
PPS 3	579999	631346	673115	712993	754079
Natural	579,999	587,851	591,395	591,025	588,217

Figure 11 Validated Population Projection Result for Oklahoma City

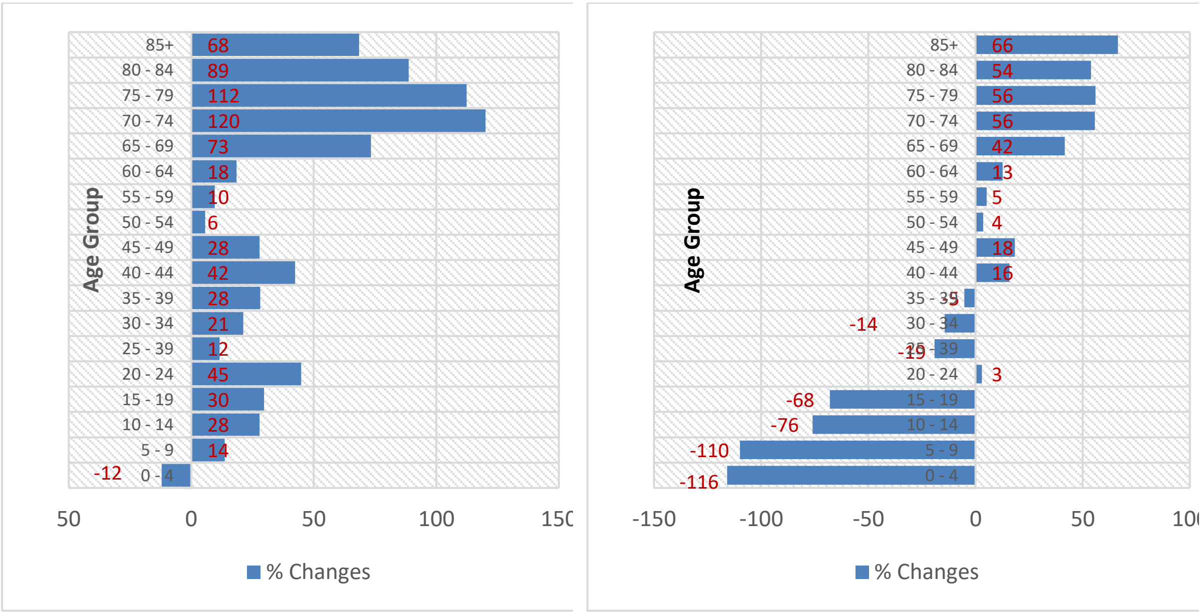
Figure 12 shows the percentage of population change per age group between 2010 and 2030 projection in various scenarios. It is shown clearly in all charts that the biggest increased population in 2030 is attributed to the elderly (65+ years old). On the other hand, the young population (0 – 4 years old) is going to decrease in all projection scenarios. This finding is accordance with the natural increase of the city depicted in Figure 12 . The city's natural increase will make the city loose big number of young population (particularly 0 – 23 years old) and left the city with high number of elderly (65+ year). This could happen due to low birth rate and long life expectancy (up to 76 years old) as stated in Lewis & Burd-Sharps (2014), which means that there will be less baby born in the next 20 years while the people in general will live longer. This finding indicates that Oklahoma City will experience aging population aging in the next 20 years. In addition, the migration scenarios employed does not giving effect too much to the aging population as they show similar trend.



2010 – Scenario 1



2010 – Scenario 2



2010 – Scenario 3 2010 – Natural Increase

Figure 12 Oklahoma City Composition Changes in 2010 – 2030 Period

However, the difference between scenarios projection and the natural increase is regarding the migration component. As depicted in Figure 12, judging from the percentage changes given by the projection scenarios and the natural increase, it can be concluded that the migration gives surplus to the future population count. It can be seen also that the migrants coming into the city in the next 20 years are concentrated on the age of 0-43 years old. The migrants with 25 – 43 years old can be attributed to oil and gas mining workers as this range of age is the prime workers for the industry (BLS, 2012).

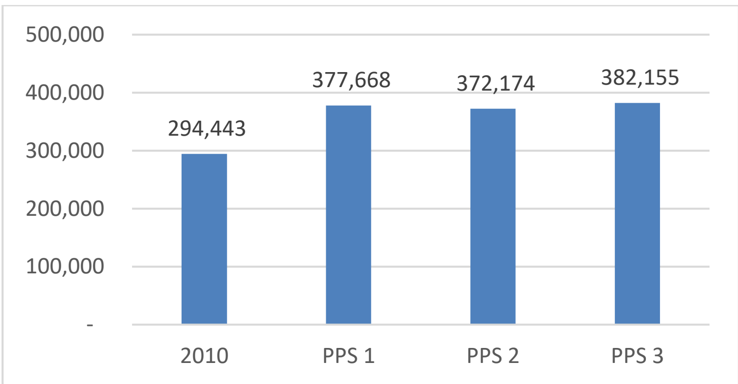


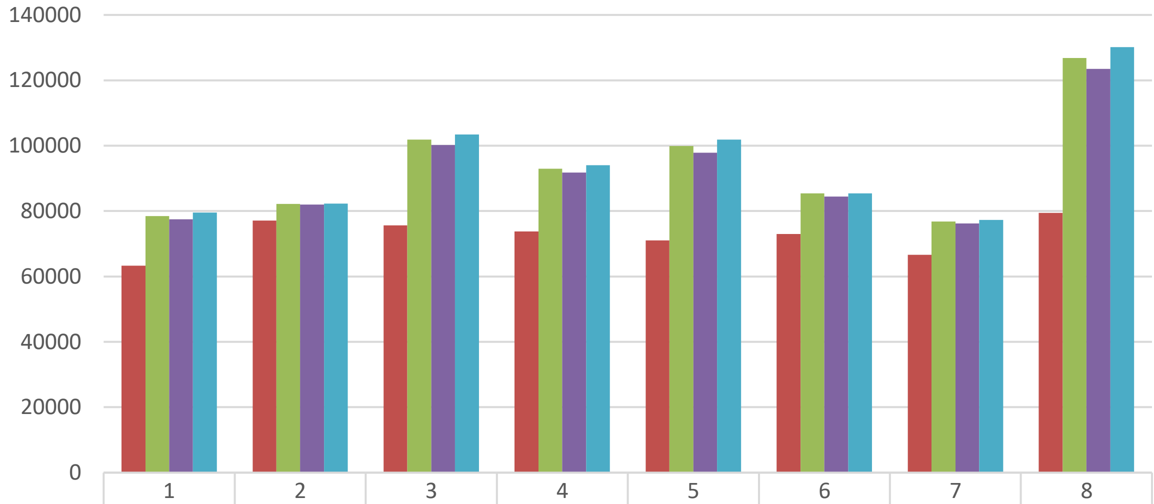
Figure 13 Oklahoma City Female Population in 2000 and 2030 (based on each PPS)

The comparison of female population in 2010 and 2030 (all PPS) for the city level is presented in Figure 13. Overall, the figure shows that the female population will increase in all PPS for 2030. Figure 1

4.4.2. Ward level

The population projection result within ward level for Oklahoma City in 2030 is presented in Figure 14. The population projection in ward level shows a similar pattern of the result in the city level. In all wards, it is projected that the population will increased with Scenario 3 yields in the highest future population numbers meanwhile PPS 2 yields in the lowest future population numbers. Nevertheless, the future population count difference between scenarios in each ward is small and not too obvious. This could mean that the effect of different migration scenarios employed does not give significant effect to the increased of population in the ward level.

Another notable observation that can be pointed is that among all the wards, ward 8 is projected to be the most populous ward (captured in all the projection scenarios). In this sense, ward 8 is expected to experience the most significant population increase in the next 20 years. Since the population growth is mainly driven by the migration, allegedly the high future population in ward 8 is caused by massive migration in the next 20 years.

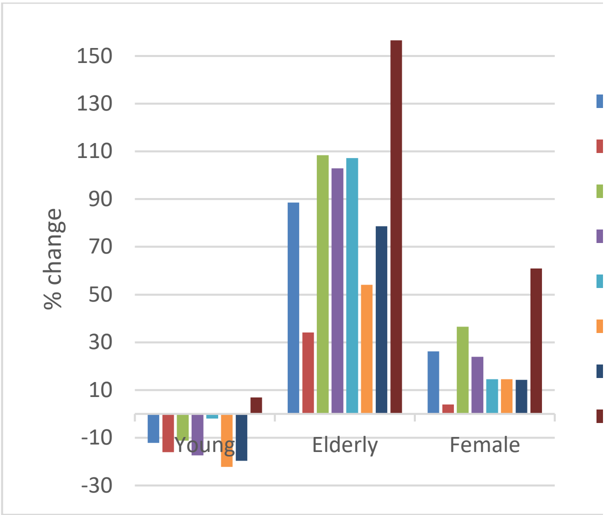


	1	2	3	4	5	6	7	8
2010	63299	77099	75676	73821	71073	72949	66643	79439
PPS 1	78519	82177	101833	92925	99874	85420	76806	126854
PPS 2	77504	82044	100251	91798	97900	84455	76264	123515
PPS 3	79535	82310	103416	94051	101847	85379	77348	130193

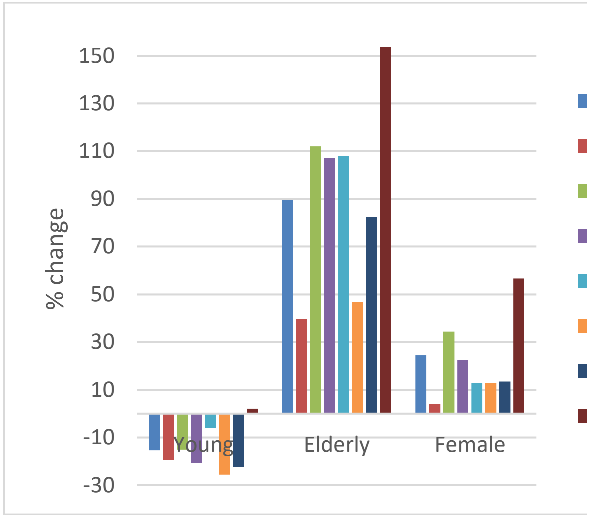
2010 PPS 1 PPS 2 PPS 3

Figure 14 Ward Level Population Projection Result

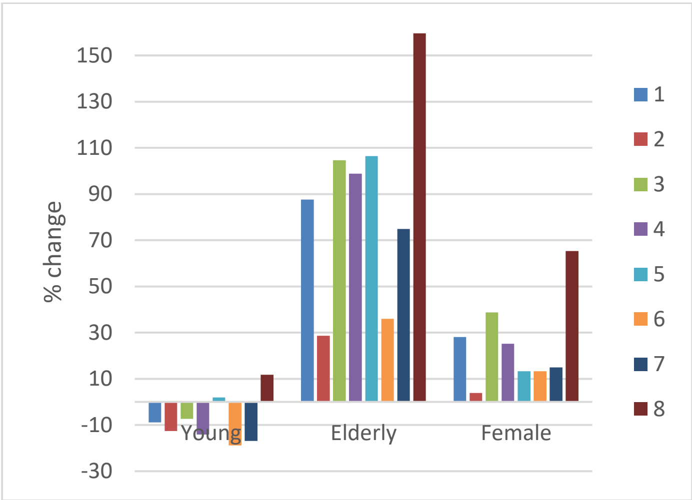
Furthermore, the changing demographic composition in ward level within the period of 2010 – 2030 in Oklahoma City can be seen in Figure 15. The figure presents the changing percentage of young (0 – 4 year), elderly (65+ year) and female population for each scenario. From this depiction, it can be observed that the young population are projected to reduce in the next 20 years in most of the wards according to all projection scenarios. In contrast, the young population reduction is not experienced in ward 8 (all scenarios) and ward 5 (PPS 3). To add, the percentage of elderly population and female population in all wards are projected to increase in the next 20 years based on all type of the projection. This finding shows that the aging population trend in the City Level is also experienced in the ward level.



2010 – Scenario 1



2010 – Scenario 2



2010 – Scenario 3

Figure 15 Demographic Composition Changes 2010 – 2030 Period in Oklahoma City

In addition, the charts in Figure 15 show that there is an increase of young population in ward 8 (in all scenarios) and ward 5 (PPS 3). Allegedly, this is happening because within these wards (in respect to the scenarios employed) there is more migration coming in the young age compared to other wards so that it gives surplus to the population count. This young age population is attributed to the family or born baby of the population in the working age, the same condition discussed in the city level. All in all, this finding shows that the employed migration scenarios are giving notable effect to the future population composition in the future.

The summary of the population composition for 2030 in each scenario is presented in Table 7 below.

Table 7 Population Composition in 2030 (in percentage)

Wards	**Scenario 1**			**Scenario 2**			**Scenario 3**		
	young	**old**	**woman**	**young**	**old**	**woman**	**young**	**old**	**woman**
1	∨ 6	∧ 20	∧ 53	∨ 5	∧ 21	∧ 53	∨ 5	∧ 20	∧ 53

2	∨ 6	∧ 16	∧ 50	∨ 5	∧ 17	∧ 50	∨ 6	∧ 15	∧ 50
3	∨ 8	∧ 15	∧ 51	∨ 6	∧ 15	∧ 51	∨ 6	∧ 14	∧ 51
4	∨ 7	∧ 16	∧ 49	∨ 5	∧ 17	∧ 49	∨ 6	∧ 16	∧ 49
5	∨ 7	∧ 18	∧ 39	∨ 5	∧ 19	∧ 39	∧ 5	∧ 18	∧ 38
6	∨ 7	∧ 10	∧ 46	∨ 6	∧ 10	∧ 45	∨ 7	∧ 9	∧ 45
7	∨ 6	∧ 19	∧ 52	∨ 5	∧ 20	∧ 52	∨ 6	∧ 18	∧ 52
8	∧ 8	∧ 20	∧ 53	∧ 5	∧ 20	∧ 53	∧ 5	∧ 20	∧ 53

Note: ^ increased percentage from 2010, ˅ decreased percentage from 2010

5. PROJECTION OF FUTURE POPULATION DENSITY

This chapter explains the process of estimating high resolution future population density in Oklahoma City. It starts with estimating the population density of each the settlement class. Next, the chapter continues with GIS-based CA model development and it ends with the population disaggregation process.

5.1. Estimating Population Density of the Settlement Land Use Classes

Estimation of the settlement's land use classes was done by taking sample of the areas that represent the settlement land use classes. Based on the land use map generated in Chapter 3, there are 3 main land use classes in Oklahoma City: settlement, commercial, and vacant land. The process began by selecting the census tracts with settlement land use class dominance. This was done by calculating the ratio between the settlement area and commercial area with the vacant land. The census tracts with ratio of settlement area more than 0.8 then selected for further sampling process. The step then continued by selecting the census tract that represent the best one of the settlement land use class (low, middle or rural) with the criteria of (Tenerelli et al., 2015):

$$\mathbf{a_{cg} / A_g - a_{no\ pop\ g} > 0.80}$$

where: "a_{cg}" is the area of the urban land use class c in the census tract g, "c" is one of the land use classes, "A_g" is total area of the census tract g and "$a_{no\ pop\ g}$" is the total area of no population class in the census tract. The result of this process is the census tracts that represent the best each of the settlement land use class. The population density then calculated by averaging the division of population number with the area of land use C in all of the census tracts that belong to land use "c". It is important to note that due to the resolution of Landsat data that is not adequate to capture the reflectance of rural settlement area, it was impossible to do a proper estimation of the rural settlement population density. To overcome this issue, the rural settlement population density was obtained from the description of rural settlement area in Oklahoma City land use map (LUTA). This process was done by using 2010 census data due to the reason this year census data is the latest data that can be obtained. All in all, the final estimated population density for the settlement land use classes can be seen in Table 8.

Table 8 Population Density Estimation

Settlement Land Use Class	Population Density estimation (people/Ha)
Medium Density Urban	38
Low Density Urban	27
Rural Density Urban	25

The result of this step is important to determine the land allocation to project the future land use of Oklahoma City. In addition, the estimated population density will be used further in the future population distribution phase presented in Chapter 6.

5.2. GIS-Based Cellular Automata Modelling

The following section describes the development of the CA model. It includes model conceptualization, development driving factor selection, calculation of probability conversion and factor's weight definition.

5.2.1. Conceptualization

This study interested in the future land use of Oklahoma City which is observed from the city's urban growth. For this purpose, GIS-based CA model was used to simulate the spatial growth of Oklahoma City. In principal, there are two mechanisms of GIS-based CA simulation: unconstrained and constrained (Sui & Zeng, 2001; R White et al., 1997). Unconstrained-CA model refers to the condition where the conversion probability is calculated for each cell whereas in constrained-CA model, the conversion probability is calculated only for the cells that meet certain criteria (Sui & Zeng, 2001). It is understood that the "constraints" here refers to the condition that could restrict the development to occur. These constraints are added to make more reliable and realistic prediction of urban land-use patterns (White et al. 1997). The evolution of a city in reality is influenced by complex factors which exist in local, regional or global level (Yen & Li, 2001). These complex factors could refer to "constrains" in the sense of Sui & Zeng (2001) and White et al. (1997). Accordingly, the constraints can be divided further into three level: local, regional and global. Local constraints represent the cell-by-cell values or the effect of surrounding cell to the modelling process (such as neighbourhood effect), regional constraints measure (mostly with distance decay function) the influence of certain geographic phenomenon or urban facility feature, meanwhile global constraint defines the land allocation of the model (Li & Yeh, 2000).

Formulation of the constraints as variables in the GIS-based CA model requires identification of factors that influence or drive the urban growth in Oklahoma City. This part is explained further in the next section.

5.2.2. Selection of Land Use Change Driving Factors

Build upon the heat stress vulnerability concept that focus on temporal and spatial demographic changing, attention is given to the existence of the settlement area which is the place where the population reside. Accordingly, the CA model developed in this study is specifically meant to project the growth/change of Oklahoma City's settlement area in the future. Therefore, the constraint variables in the model was selected based on the factors that drive the growth of settlement area.

For this study, the driving factors are derived from the literature review and consideration of the city's development trend. The selected factors along with the logic underlying the factors selection is described as follows:

- *Neighbourhood Function*
  Neighbourhood forms the basis of any CA model (Couclelis, 1997). The neighbourhood function reflects the spatial effects of the surrounding area. In the urban growth/LUC context, this function explain that a land use class will grow or occur in the area surrounded by similar land use class. Thus, it is expected that the settlement area will grow on the adjacent or in the vicinity of the same settlement area. This mechanism also supports the expansion of the settlement area city which grows as a continuation of the urban fringe area and formed an edge-expansion growth trend.
- *Urban Centre*
  Urban centre plays an important role in the city growth as it provides resources supporting the urban activity (Yen & Li, 2001). In Oklahoma City context, the city centre is the place it where entertainment, high class housing, hospitality, retail, offices and service centre are located and makes the city centre attractive. Due to this reason, it is reasonable for the developers to build housing with proximity to the city centre. As implication, the city is growing in a more concentrated rather than dispersed manner (as mentioned in chapter 3). There is a certain degree of centrality that influenced the city growth. Thus, it is important to include the proximity as one of the variables in the CA model.

- *Urban Amenities*
  Amenities have a significant role of attracting people to come to cities. This claim has been reported in many study such as Duranton & Puga (2014), Roback (1982) and Rosen (1979). From these literatures, it is obvious that cities with better amenities will attract more people that could lead to the growth of the city. In the same manner, within the city context, the urban amenities could attract the people to live closer to it. As consequences, this idea drives the growth of the settlement closer to the urban amenities as the housing industry would use this demand as opportunity for the sake of their business. Furthermore, Gottlieb (1995) stated that amenities may be defined as place-specific goods or services that serve as utility function. This could mean social space, entertainment, tourism, education, social service, etc. In Oklahoma City context, most of these functions are covered in the urban centre area which already selected. Nevertheless, considering the massive population growth in young age coming to the city, it is necessary to emphasize more the role of education and tourism utility function. As mentioned in the background part, there are 3 big lakes within the boundary of Oklahoma City. These lakes are functioned as tourism places for the urban population to relax and as a getaway from the busy life. Thus, the urban population might want to live closer to these places to get a better access for it. Moreover, the closeness to school area is also an important consideration of the urban population to choose their living place. Reflecting to the population condition where the main force of population growth is the migration within the young age, it is important for them to live in the place that is closer to school area. This is to makes sure that they can get a proper access to a good education. Given these points, the proximity to lake and school are important to be incorporated in the model configuration.
- *Flood and river area*
  Oklahoma City is located in a riparian area. That is why there are rivers, streams and lakes in the city's landscape. In general, the condition of a piece of land located in the flood area will reduce the value of the land and it will be less attractive for the developers. Thus, this clearly becomes a constraint for the development and it is important to be incorporated in the model configuration.
- *Transportation*
  Transportation is obviously one of the essentials factors of urban growth. This claim has been investigated in many research such as Becker et al. (2006) and Burchfield et al. (2006). The growth of the city most likely will also follow the existence of the road because it serves as the main infrastructure to transport goods and materials. However, considering the hierarchy of the road and the purpose of the model (focus on the settlement area), not all type of the road was used in the model configuration. For that matter, the arterial road was selected as one of the driver factors. The reason for this selection is because the arterial road is the pioneer of all roads and the network reaches the entire area of the city. Thus, with this characteristic, it is expected that the growth of the city will happen in the vicinity of the arterial street.
- *Land Consumption*
  The land consumption defines the total area dedicated for the development. This factor is important as it determines how much area will be developed in the upcoming years. In CA model, this factor controls the amount of growth in each iteration throughout the entire time frame.
- *Zoning area*
  The municipality of Oklahoma City has set a zoning area that constitutes the usage of each land parcel (LUTA). These zoning area polygon is obtained from the municipality of Oklahoma City website (www.okc.com) which includes the zoning for rural settlement, urban settlement, commercial, industrial and agriculture land use. In this sense, the zoning area is being a guidance for the development of these land uses to take place.

All in all, these driving factors are grouped based on their characteristic according to the definition of local, regional and global constraint by (Li & Yeh, 2000). The result of this grouping is presented in Table 9.

Table 9 Constraints Factors

Component	Local	Regional	Global
Neighbourhood	Neighbourhood function	-	-
Zoning Area	City Boundary, Urban Settlement Area, Airport and Military Area	-	-
Environment	Flood and River area	-	-
Urban Center	-	Distance to downtown	-
Amenities	-	Distance to school, distance to lake	-
Accessibility	-	Distance to arterial road	-
Land Consumption	-	-	Land Allocation

Finally, these factors are used to calculate the conversion probability which will be described further in the following part.

5.2.3. Conversion Probability and Transition Rules

All the constraints explained in the previous part were treated separately to produce the conversion probability value (the driving factors maps are presented in Figure 16 :

- Starting with the zoning area, the land use raster data is subtracted (in ArcGIS) from the boundary of small cities, airport and military base. This is to make sure the modelled land use class does not interfere with these areas as their primary functions are not the subject of the model. Next, since the increased population is subject to the increase of the urban settlement, practically, urban settlement zone is being the basic zoning area for the model. In the model configuration, the urban settlement zone is given value "1" meanwhile the other zone is given value "0". Furthermore, flood and river area is becoming a barrier for the development in the sense that it makes a piece of land unattractive to be developed but it does not make the development will not occur in those areas. Therefore, the area of flood and river zone area given value "0.5" meanwhile other area is given value "1". All in all, the treatment of these local constraints resulted in a composite map that serves a suitability map for settlement development in Oklahoma City.
- Next, all of the factors in regional constrain is calculated using decay function. For this purpose, Euclidean distance that represent the distance/proximity to the selected factors such as lakes, downtown, school and arterial road was calculated.
- Lastly, the land consumption is derived from the result of the population projection. This part will be elaborated further in the next section.

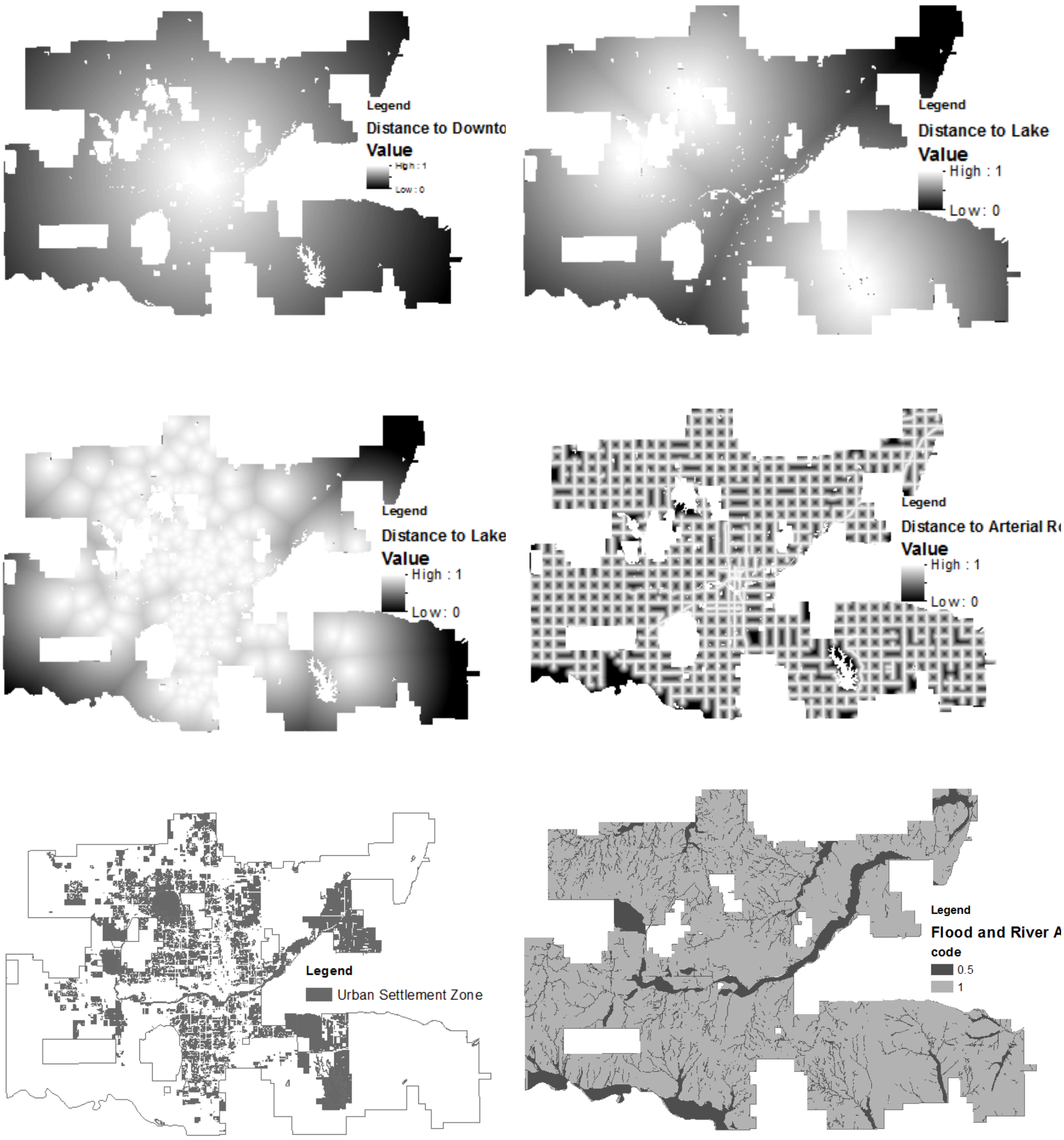


Figure 16 Driving Factors

Next step of the process is to calculate the conversion probability. For this purpose, Multicriteria evaluation techniques was employed to obtain the conversion probability (Wu & Webster, 1998; Yen & Li, 2001). Following this method, the conversion probability for each cell is defined as:

$$\mathbf{CPi = ((\alpha1*lake + \alpha2*downtown + \alpha3*main\ road + \alpha4*neighbourhood)/\ (\alpha1+ \alpha2+ \alpha3+ \alpha4))\ *suitability}$$

CPi is the conversion probability form vacant land to urban settlement; $\alpha1$, $\alpha2$, $\alpha3$ and $\alpha4$ are the weight of each factor; lake, downtown, road variables area the Euclidean distance to the nearest lakes, school zones, and main road; meanwhile the neighbourhood variable is the value of neighbourhood effect calculated with rectangular 3x3 grid cells moving window; and suitability is the value of 1 (urban settlement) or 0 (non-urban settlement). To operate this formula, the value for lake, downtown and main road should be normalized to be uniform with the value of the neighbourhood function. The normalization was done using minimum maximum method (Voogd, 1983). Later on, the calculated value was divided with the sum of the factor's weight to obtain the weighted-average score of the CPi. Lastly, the result is multiplied with the suitability score (1,0) to make sure the conversion probability is calculated for the pixel that suits the settlement allocation.

Next step is to apply the transition rule. The state of the cell is decided by comparing the probability of the conversion with a predefined threshold. There is only a binary value for the transition: developed (1) or not developed (0). If the value is higher than the threshold, then it is classified as developed and if the value is lower, it is classified as undeveloped. Later on the cell is converted to this state, subject to the global constraints (as demonstrated in White (1998)). For this study, a simple calculation model (made in ArcGIS model builder) is used to iteratively define the threshold and convert the cells accordingly to get the desired cell allocation.

5.2.4. Defining the factor's weight

The factor's weights are calculated by using multinomial logistic regression. The process started with making a pseudo panel. This panel is a table that comprises cross section of locations (build and unbuilt), including the affecting variables (in this case its 2000 and 2010). First, point samples are taken by creating random points of the study area. Next, the urban settlement land use and vacant land in year 2000 and year 2010 were reclassified so that the urban settlement land use is valued 1 and vacant land is valued 0. The classified values then extracted into the point samples. These values are used to represent the amount of vacant land that is converted into urban settlement within 2000 – 2010 period and will be the input to create the dependent variable in the regression calculation. Furthermore, the normalized values of lake, school and main road variables are also extracted into the point samples. These values are used as independent variables in the regression analysis. The point samples data then imported to excel data and this data is the pseudo panel mentioned before. Prior to the multinomial regression calculation, the data was tested for multicollinearity and the result shows that there is no multicollinearity found as the VIF value of all variables are below 10 according to Field (2009).

Next, the multinomial regression analysis was performed using this data. This step resulted in the weight of each factors. These weights then incorporated to the conversion probability formula to calculate the probability of each cell. The result of the regression can be seen in Appendix C meanwhile the weight of each factor presented in Table 10.

Table 10 Weight of the Factors

Component	Weight	
	Vacant - Medium Settlement	**Vacant – Low Settlement**
Arterial street	4.691	4.832
School Area	21.881	1.865
Lake	2.636	.335
Distance to Downtown	-9.991	-.186
Neighbourhood	17.694	5.800

This is important in the modelling process as the values (weights) produced by the multinomial logistic regression analysis represents the influence of each factors on how the vacant land was converted into the urban settlement. In this sense, this part is considered as the calibration of the GIS-based CA model for Oklahoma City.

5.2.5. Projection of Future Land Use in Oklahoma City

The projection of future land use in Oklahoma City is made upon the following considerations. Firstly, as discussed in previous section, the focus point of the model is regarding the growth of the settlement area. Therefore, the model simulation was solely run to project the future settlement area. Secondly, it was defined that the increased population is subject to the growth of the urban settlement rather than rural settlement. This is due to the assumption that the people coming to the city mostly attracted to the urban living style which means that they want to live in the urbanized settlement and not in the rural area. Practically, this makes low and medium density urban settlement being the specific settlement land use class modelled in this study.

The projection of future land use in Oklahoma City is built upon scenarios of land allocation that represent the city's possibilities of growth. Therefore, the land use change model is simulated following different land allocation for low and medium density urban settlement. This land allocation was derived based on their proportion of population increased. The proportion was calculated by comparing the multiplication of the population density with the increased area of each urban settlement classes (see Table 11). At the end, the total land allocation for 2010 – 2030 is calculated by multiplying the proportion of each urban settlement class with the increased population of all population projection scenarios in the same time frame. The final land allocation of this scenario can be seen in Table 11.

Table 11 Land Allocation

2000 – 2010 Period				
Urban Settlement Classes	Area Increased	Population Density	Population Increased	Proportion
Low	618	27	130.464	0.6
Medium	7096	38	70.87	0.4
Land Allocation for 2030 period				
Urban Settlement Classes		Population Projection Scenario		
		1	2	3
Low		3654	3416	3868
Medium		1731	1618	1832

Next, the conversion probability value was calculated using the weight from the regression analysis that describes the changing from vacant land to low density urban settlement (from Table 10). After that, the new developed land is allocated according to the land demand of each projection type. In addition, we simplify the model simulation by running the model statically (in one run for 20 years) without the iterative process. This way the simulation time is reduced and it still produced meaningful result (even though it is less precise) with less uncertainty (the result is more aggregated).

To add, the model was simulated by incorporating 2 development scenarios, which were formulated based on 2 documents: the analysis of Oklahoma City future growth reported by ECONorthwest (2014) and the Planokc document. In that document, it was reported that there are three possible growth scenarios. The first scenario was made according to the historical trend of the city which has resulted in a low-density expansion on the fringe of the city. The second and third scenarios are meant to address the changing of housing market that supports the high-density development. The high-density development in scenario 2 and 3 is reflected upon the current plan of revitalizing the old city centre that would attract people to come and live closer to the city centre. Given these points, there are two LUC scenarios employed in the model: sprawl and dense. The sprawl scenario (LUCS 1) refers to the current development growth that reflects sprawl type of growth meanwhile the compact scenario (LUCS 2) reflects the high-density development that could lead to a denser and concentrated development by maximizing the effect of the downtown. The difference of both scenarios is regarding the weight of the distance to downtown (as presented in Table 10). The sprawl scenario use the weight of distance to downtown variable as listed in Table 10. Meanwhile, to reflect the effect of revitalized downtown in the dense scenario, the weight of distance to downtown was set the same as the highest variable weight in each urban land use classes in the dense scenario model.

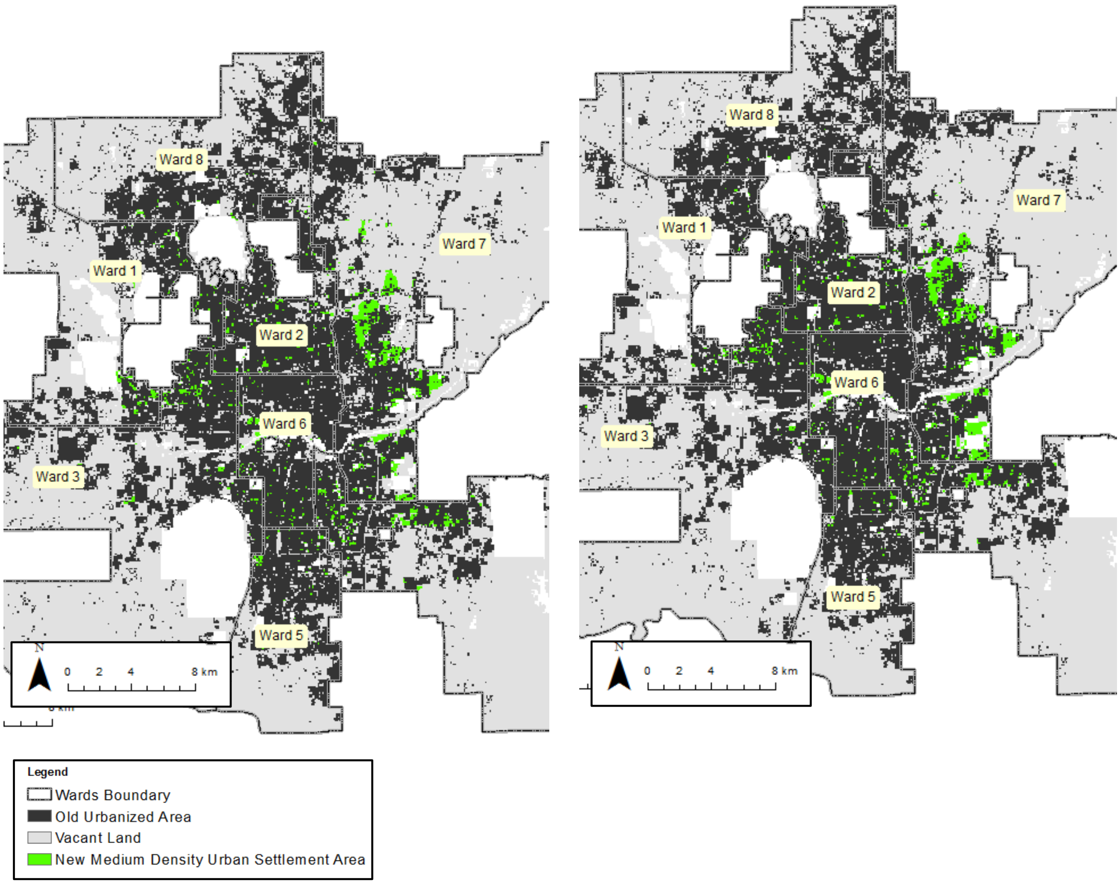
The simulation result of all the development scenarios which also incorporating the population scenarios result. Therefore, there are 6 combination of simulation as listed in Table 12.

Table 12 Land Use Change Scenario Combination

Land Use Change Scenario (LUCS)	Population Projection Scenario (PPS)	Combination
1 (sprawl development)	1 (current trend)	LUCS 1 – PPS 1
	2 (decreased migration)	LUCS 1 – PPS 2
	3 (increased migration)	LUCS 1 – PPS 3
2 (compact development)	1 (current trend)	LUCS 2 – PPS 1
	2 (decreased migration)	LUCS 2 – PPS 2
	3 (increased migration)	LUCS 2 – PPS 3

5.2.6. Land Use Projection Result

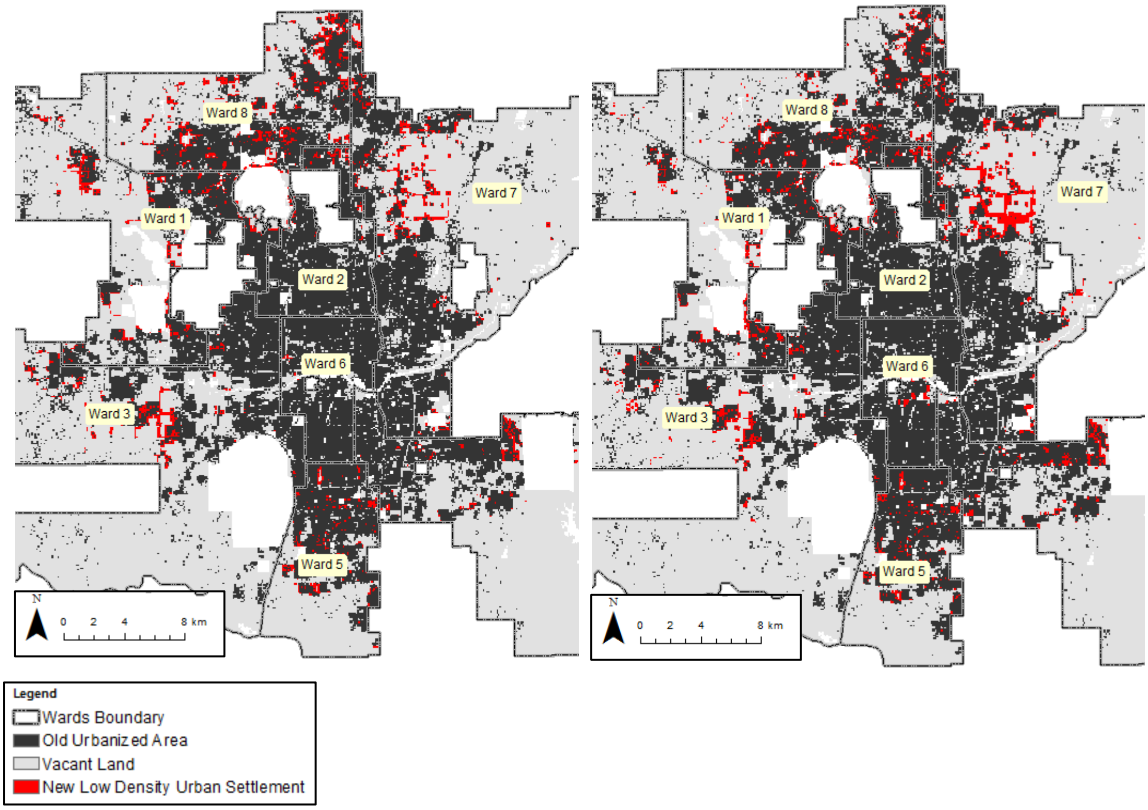
The explanation of the LUC simulation result is divided per urban settlement class. For the medium density urban settlement class, both LUCS scenarios in all PPSs resulted in the same development pattern of the new medium density urban settlement. Since the results are similar for all simulation combination, we showed the result with the most distinguishable difference presented in Figure 17, whereas the complete result can be seen in appendix D. It is predicted that most of the growth occur on the east and northeast of the city, particularly around the North Canadian River which is located in Ward 7 area. There is also some infill-development pattern can be found from the figure on both LUC scenario projection result. For the sprawl scenario, the medium settlement area is projected to grow towards the nearest vacant land where there are many school. This is because of neighbourhood function and the proximity to school are the most significant variables variable. On the other hand, regarding the result for LUCS 2 in a glance the development pattern is similar with LUCS 1. However, it is projected that there will be more developed area on the southern part of the North Canadian River. This reflects that the revitalization of the downtown would create more development on the northern and southern side of the river. This difference is because of the high weight of distance to downtown which affecting the development in a radial pattern that produce new medium density settlement area pattern as depicted in **Error! Reference source not found.**. To add, the population projection scenarios do not affect the development growth pattern as they just determine the land allocation. The different land allocation as consequences of different population projection scenarios depict similar development pattern in each LUCS.



LUCS 1 – PPS 3   LUCS 2 – PPS 3

Figure 17 Medium Density Land Use Simulation Result Example

Next, the results of the low density urban settlement projection show different development pattern of the new low density urban settlement area for LUCS 1 and LUCS 2. To show this difference, we presented the result with the most obvious difference in Figure 18 meanwhile the full result can be seen in Appendix E. In the sprawl scenario, it seems like the growth occur in all parts of the city. On the northern and north-western part of the city (ward 1 and ward 8) the growth occurs as the continuation of the urban fringe. This is as expected from the effect of the neighbourhood function as one of the most significant variable. It can be seen also that there is new developed land that grows following the road pattern and far from the city's urban area. Development in this area happened because the effect of proximity to road as well as the land use zoning. In the compact scenario, it is highly noticeable that there would be a massive growth on the north-eastern part of the city which is in the area of ward 7. This captured phenomenon happened because of the effect from the modified distance to downtown weight to reflect the effect of downtown revitalizations (as the main assumption in LUCS2). The downtown revitalization effect would drive development to be focused on the vacant land located in the nearest distance (radially) to the city center. To add, similar with the medium density urban settlement simulation, the population projection scenarios do not affect the development growth pattern as they just determine the land allocation.



LUCS 1 – PPS 3

LUCS 2 – PPS 3

Figure 18 Low Density Land Use Simulation Result Example

The summary of the new area development for low and medium density development by numbers for all simulations is presented in Table 13.

Table 13 Increased Area of Low and Density Urban Settlement Area (in Ha)

Wards	LUCS1 - PPS 1		LUCS1 - PPS 2		LUCS1 - PPS 3		LUCS2 - PPS 1		LUCS2 - PPS 2		LUCS2 - PPS 3	
	Low Urban	Medium Urban	Low Urban	Medium Urban	Low Urban	Medium Urban	Low Urban	Medium Urban	Low Urban	Medium Urban	Low Urban	Medium Urban
1	127	668	112	641	140	686	49	585	42	601	53	613
2	158	108	157	106	166	103	149	135	146	137	154	131
3	156	465	150	420	164	486	140	430	136	473	144	461
4	222	403	203	301	249	470	213	281	189	318	227	283
5	59	306	55	308	67	302	55	312	45	319	63	307
6	134	15	124	19	137	13	160	0	160	58	160	0
7	817	768	767	716	872	828	951	1184	880	1133	982	1339
8	29	920	26	877	31	936	13	666	13	669	13	689

Note: Higher Increase

5.3. Population Disaggregation

The following part will explain regarding the population disaggregation using dasymetric mapping technique. The discussion comprises of description about the method of dasymetric mapping itself followed by the result and interpretation.

5.3.1. Dasymetric Mapping

The population disaggregation method used in this research followed the method of dasymetric mapping by Mennis (2009), Peña (2012) and Nelson (2004). This technique interpolates the statistical data in coarse resolution (ward) into the desired unit (100 m resolution) by using land use area fraction as proxy to assign number of population in each of the grid cell. In this study, the area fraction is derived from the density of the settlement classes (rural, low, and medium density urban settlement). This method was applied for all the population and LUC scenarios. The process began with calculating the fraction of the total population that should be assigned for each of the settlement classes within the ward:

$$\mathbf{d_{uz} = (p_{uz}) \ / \ (p_{hz}+p_{lz})}$$

Where "d_{us}" is the fraction of a settlement class in city level, "p_{rs}" as the population density of rural settlement class, "p_{ls}" is the population density of low urban settlement class, and "p_{ms}" is the population density of high urban settlement class. Next step is to calculate the percentage of a wards' total area that is occupied by a certain settlement class, divided by the assumed percentage of 50%:

$$\mathbf{a_{sa} = (n_{sa}/ \ n_a)/ \ 0.5}$$

With "a_{sa}" area ratio of a settlement class *s* in ward a, "n_{sa}" as the number of grid cells of settlement class "s" (rural/low/medium density urban settlement) in ward "a" (1/2/3/4/5/6/7/8), n_a = number of grid cells in district a. Furthermore, the total the fraction of a wards' total population that should be assigned to one of the three settlement classes in ward level were calculated with:

$$\mathbf{f_{sa} = (d_{rs} * \ a_{ra})/ \ [(d_{rs} * \ a_{ra}) + (d_{lc} * \ a_{la}) + (d_{mc} * a_{ma})]}$$

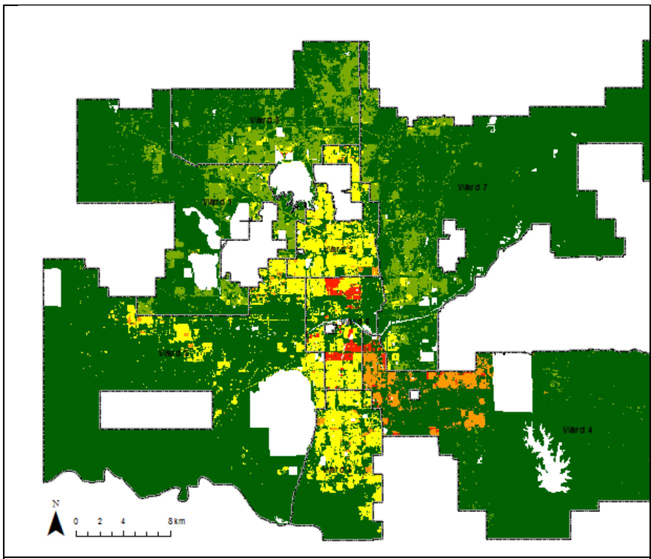
With "f_{sa}" as the total fraction of a settlement class "s" in ward "a", "d_{rs}" is the fraction of rural settlement, "a_{ra}" as the area ratio of rural residential class in ward "a", "d_{lc}" as the population density fraction of low urban settlement class, "a_{la}" as the area ratio of low density urban settlement class in ward "a", "d_{mc}" as the population density fraction of medium urban settlement class and "a_{ma}" as the area ratio of low density urban settlement class in ward "a". Last step is to assign the population value for each grid based on the fraction calculation in respect to the settlement classes and wards:

$$\mathbf{pop_{ra} = (f_{ra} * \ pop_a)/ \ n_{ra}}$$

with "pop_{sa}" as the number of population assigned to one grid cell of settlement class "s" in district "a", "f_{sa}" as the total fraction of a settlement class "s" in ward "a", "n_{ra}" as the number of pixel of settlement class "a" and "pop_a" as the total population number of ward "a".

5.3.2. Result

The result of this process is the population density map in 2010 and 2030 condition of all simulation combination (referring to Table 12). These results are mapped and presented in Figure 19.



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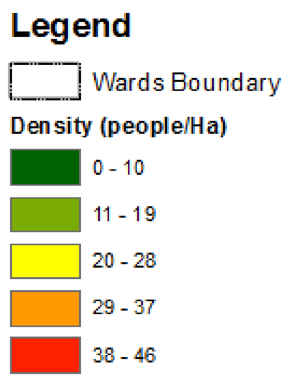

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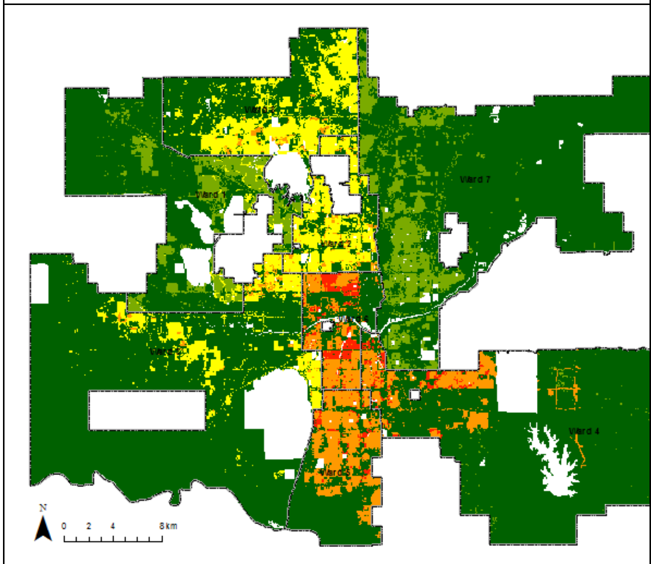
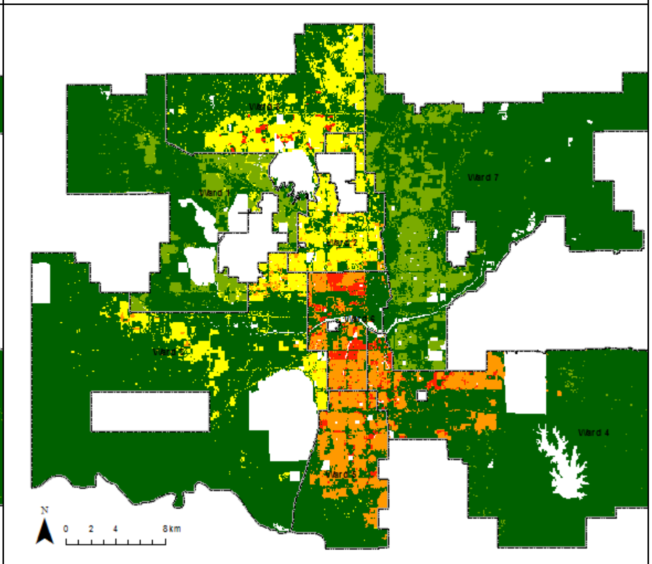
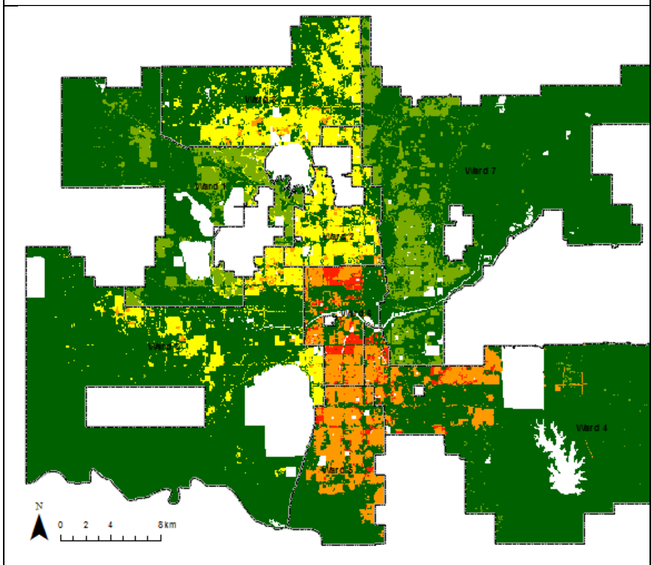


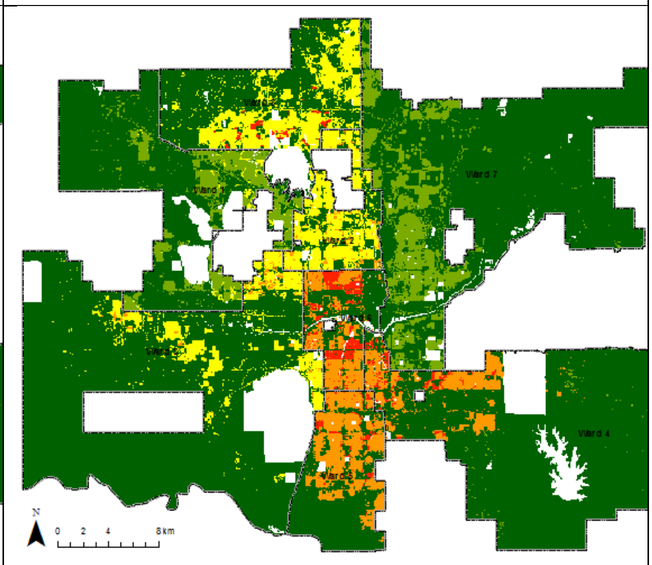
LUCS 1 – PPS 1



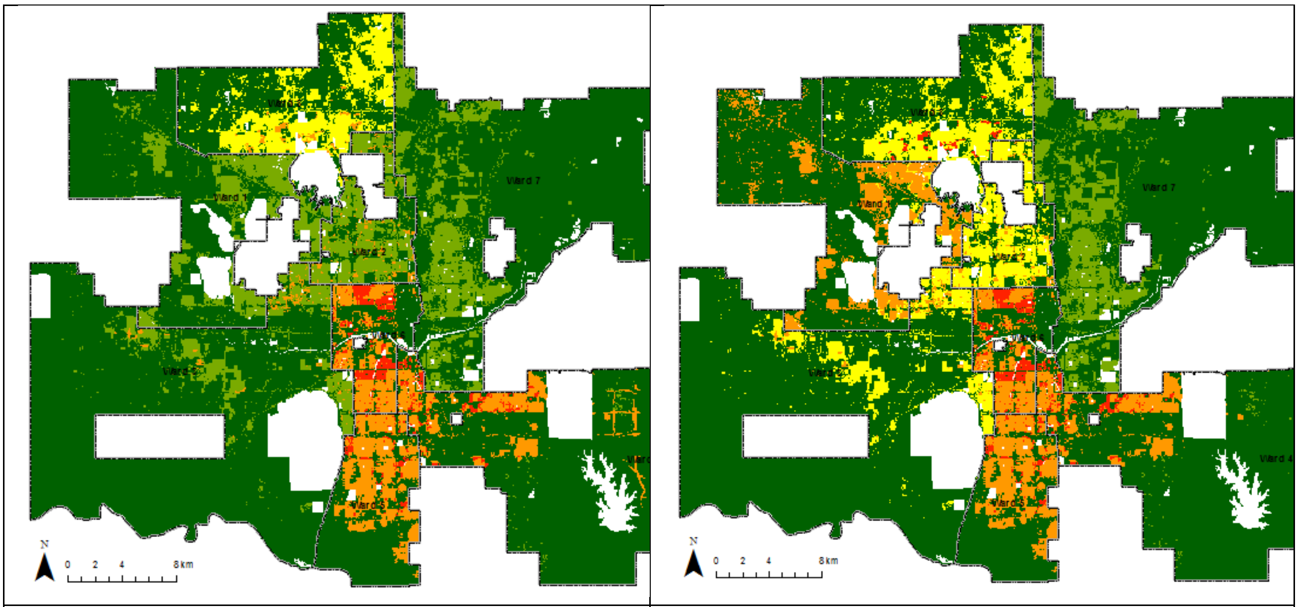
LUCS 2 – PPS 1



LUCS 1 – PPS 2



LUCS 2 – PPS 2



LUCS 1 – PPS 3	LUCS 2 – PPS 3

Figure 19 Dasymetric Mapping Result

Based on the figure, there are several observation points that can be made. In LUCS1 – PPS 1, LUCS1 PPS 2 and LUCS 1 – PPS 3 simulation, most of the area in ward 5 and 6 will experience increased density. This mostly because of these wards are experiencing increased but there is no significant increase of urban area (low and medium urban settlement). In contrast, ward 2 and 3 in LUCS1 – PPS 3 are experiencing decreased density. This is happening because the increase of urban area is more significant than the increase of the population. As the consequences, the population is more distributed.

Moreover, focusing on the land use change scenario 2, LUCS 2 – PPS 1 and LUCS 2 – PPS 2 reveal the same pattern of density. This means that there is no significant change in both population numbers and urban area. On the other hand, as seen in LUCS2 – PPS 3, ward 1 is experiencing increased density. This indicates that there is a significant increase of population with less new urban area.

6. CURRENT AND FUTURE COMPOSITE VULNERABILITY INDEX

This chapter explains the process of current and future composite vulnerability index calculation. It starts with explanation regarding the conceptualization of the index. Next, the chapter continues with explanation of the urban heat wave vulnerability indicator and it ends with the explanation of the result.

6.1. Conceptualization

To see the effect of demographic change to heat stress urban vulnerability, composite index of exposure and sensitivity index for the current condition and future condition is calculated. It begins with deriving the required information of the selected vulnerability variables (the future number of elderly population (>65 years old), young population (<5 years old), female population) into the 100-m grid level. For the current condition index, the required data is derived by multiplying the percentage of each variables obtained from the age and sex based population count in 2010 census, with the population density in 2010. On the other hand, for the future condition index, the required data is derived by multiplying the percentage of each variables obtained from the age and sex based projected population count in respect to the applied population projection scenarios and LUC scenarios. This process will be elaborated further in the next section.

The next step of the vulnerability index calculation was normalizing the data of both condition (current and future) based on each variable. The normalization was done using minimum maximum method (Voogd, 1983). The final score is obtained by the sum of the normalized indicator value multiplied by the weight of each variable. In this study, equal weight allocation is applied to determine the weight of the selected variables (Morabito et al., 2015). This treatment was used because to avoid subjectivity due to lack of data and resource. Accordingly, the variables' weights are presented in Table 14.

Table 14 Weight of the Selected Vulnerability Variable

Element	Weight	Variable	Weight
Exposure	50%	Population Density	50%
Sensitivity	50%	Young	16.7%
		Elderly	16.7%
		Female	16.7%

Finally, the index calculation can be described mathematically as:

Total score = (NV. Population density*weight1) + (NV. Young*weight2) + (NV. Elderly*weight3) + (NV. Female*weight4)

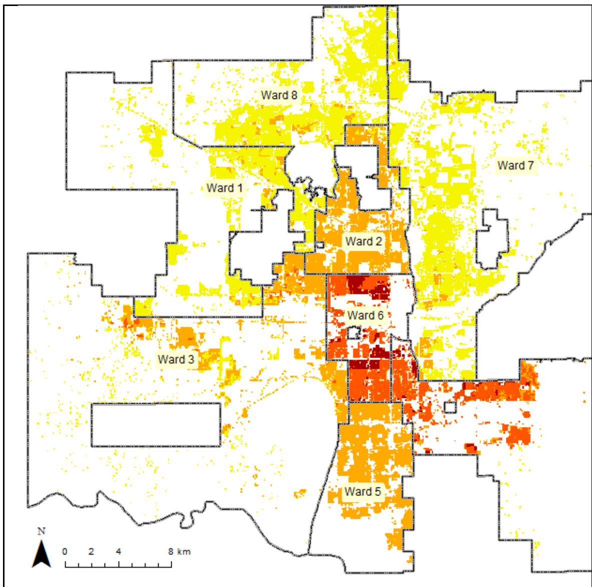
With, "NV" as the normalized value, "weight 1" as the weight of population density variable, "weight 2" as the weight of young population variable "weight 3" as the weight of elderly variable and "weight 4" as the weight of female variable.

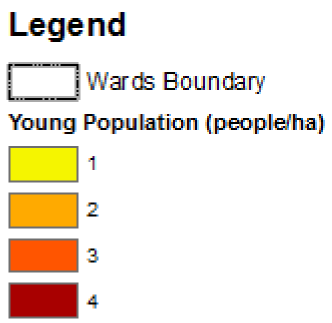
6.2. Urban Heat wave Vulnerability Indicators

The following part discusses the vulnerability indicators in 100-m grid for the current and future condition. These indicators are derived from the current and future population numbers following the method mentioned in the previous section. The discussion in this section is divided per vulnerability indicator.

6.2.1. Young Population

The maps of young population data (0 – 4 years old) for current (2010) and future condition (2030) in regards to the various simulation combination (as stated in Table 12) are presented in Figure 20. The disaggregated 100-m grid young population data resulted young population density from 1 – 4 people / ha. As shown in the maps, the combination of population projection scenarios and LUC scenarios resulted in a different pattern. LUCS1 – PPS 1 and LUCS2 – PPS 2 resulted in a similar pattern of young population distribution. In these scenario combination, compared to 2010 condition, it is identified the young population density is decreased condition in most of the area in ward 2, 4, 5 and 6 meanwhile the young population density is increased most of the area in ward 8. Next, LUCS1 – PPS 2, LUCS1 - PPS 3, LUCS2 – PPS 2 and LUCS2 – PPS 3 resulted in a similar pattern showing a decreased young population density (compared to 2010 condition) in most of the area of ward 2,3,4,5,6. This different pattern is mostly attributed to the multiplication of different composition change (resulted from the population projection scenarios) with the estimated high resolution population density. The fact that there is a notable difference in population projection 1 in both LUCS indicates that the population projection scenario influence more the 100-m grid elderly population data rather than the type of LUC scenario employed.





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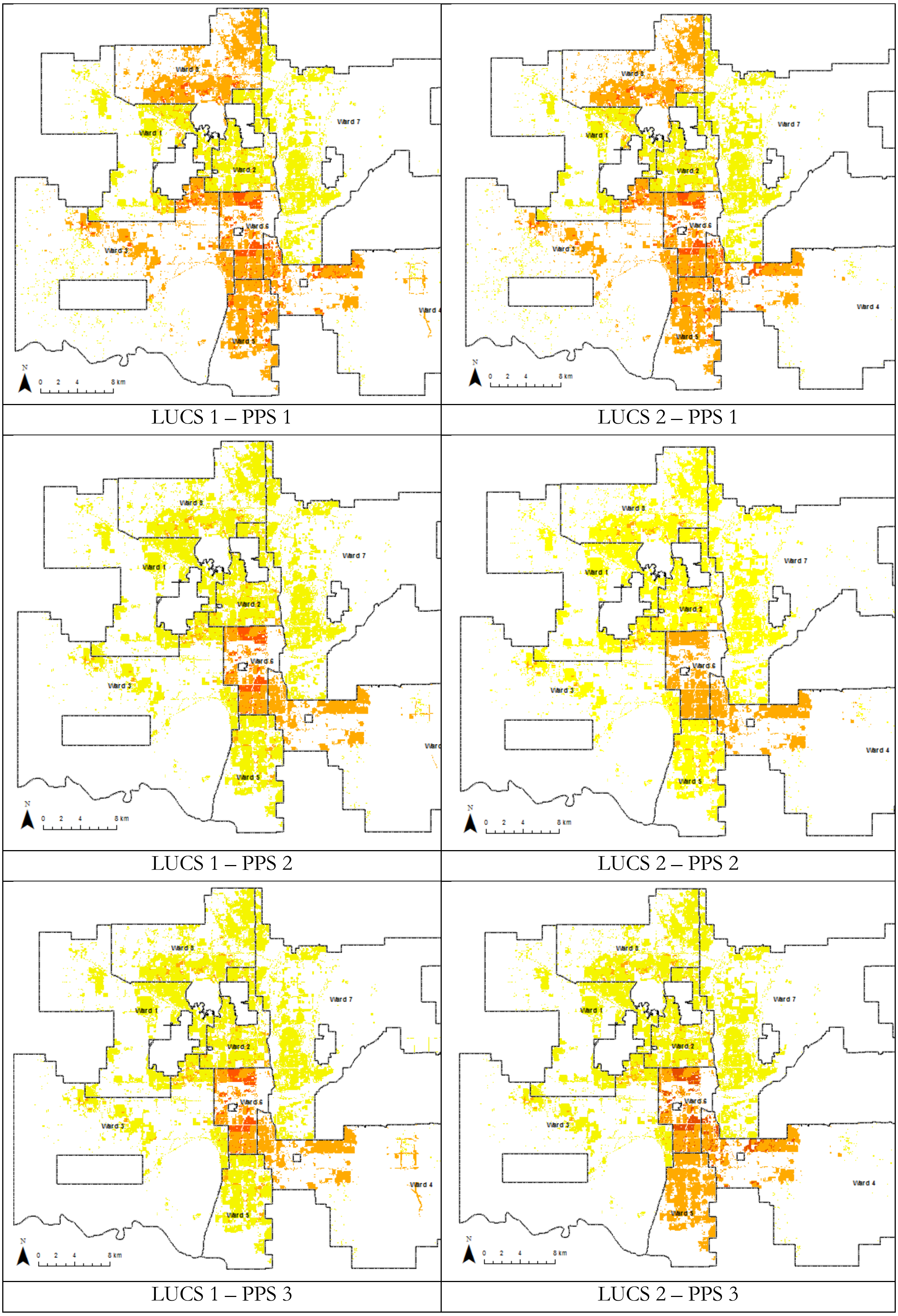
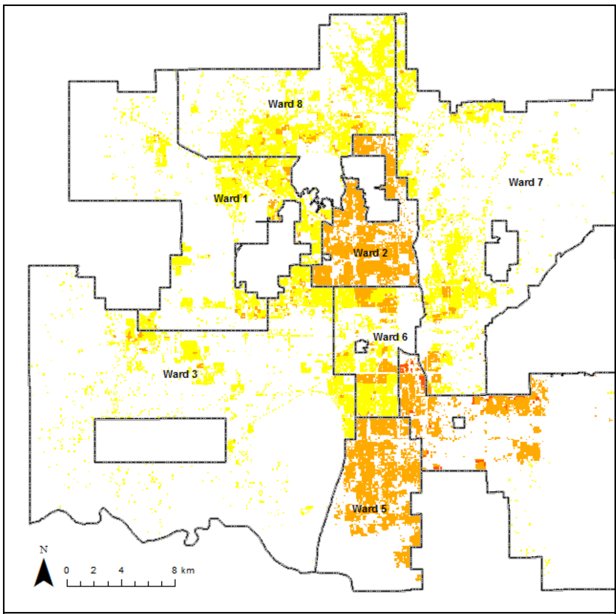


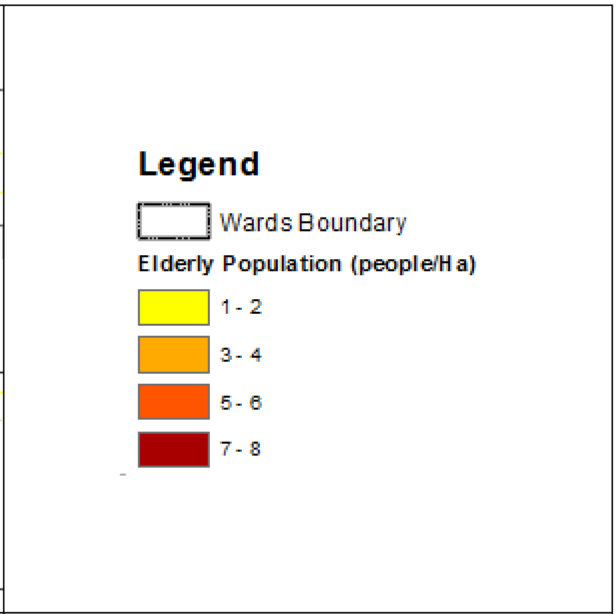
Figure 20 Young Population Urban Vulnerability Indicator

6.2.2. Elderly Population

The maps of elderly population data (65+ years) for current (2010) and future condition (2030) in regards to the various simulation combinations (as stated in Table 12) are presented in Figure 21. The disaggregated 100-m grid elderly population data resulted in the elderly population density with 4 classes: 1-2 people/ha, 3-4 people/ha, 5-6 people/ha and 7-8 people/ha. Compared to 2010 condition, the maps show that the elderly population is increased in most of the area in ward 1,3,4,5,6 and 8 which is captured in all simulation combinations. This indicates that in 100-grid level, different migration scenarios coupled with sprawl or compact scenario reveal a similar trend showing increased elderly population in theses wards.



2010



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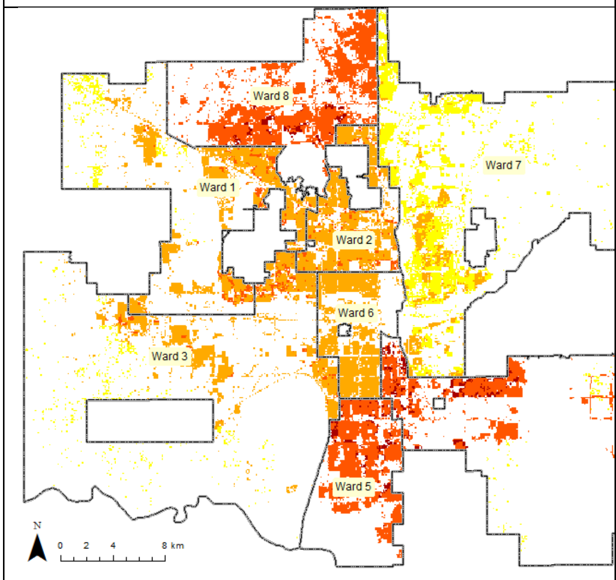
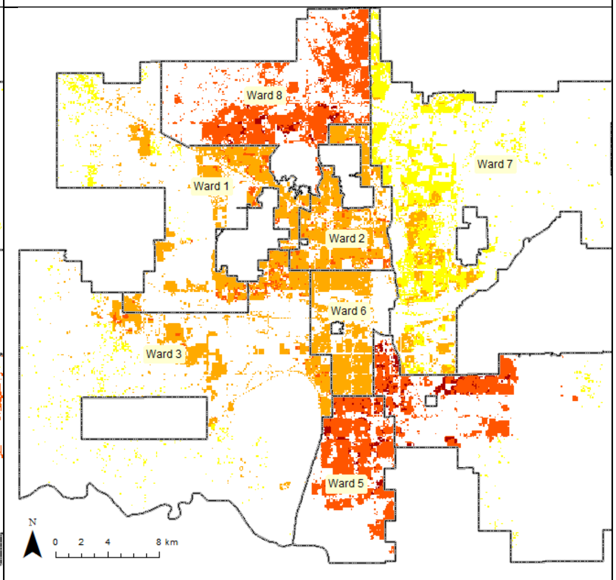


LUCS 1 – PPS 1



LUCS 2 – PPS 1

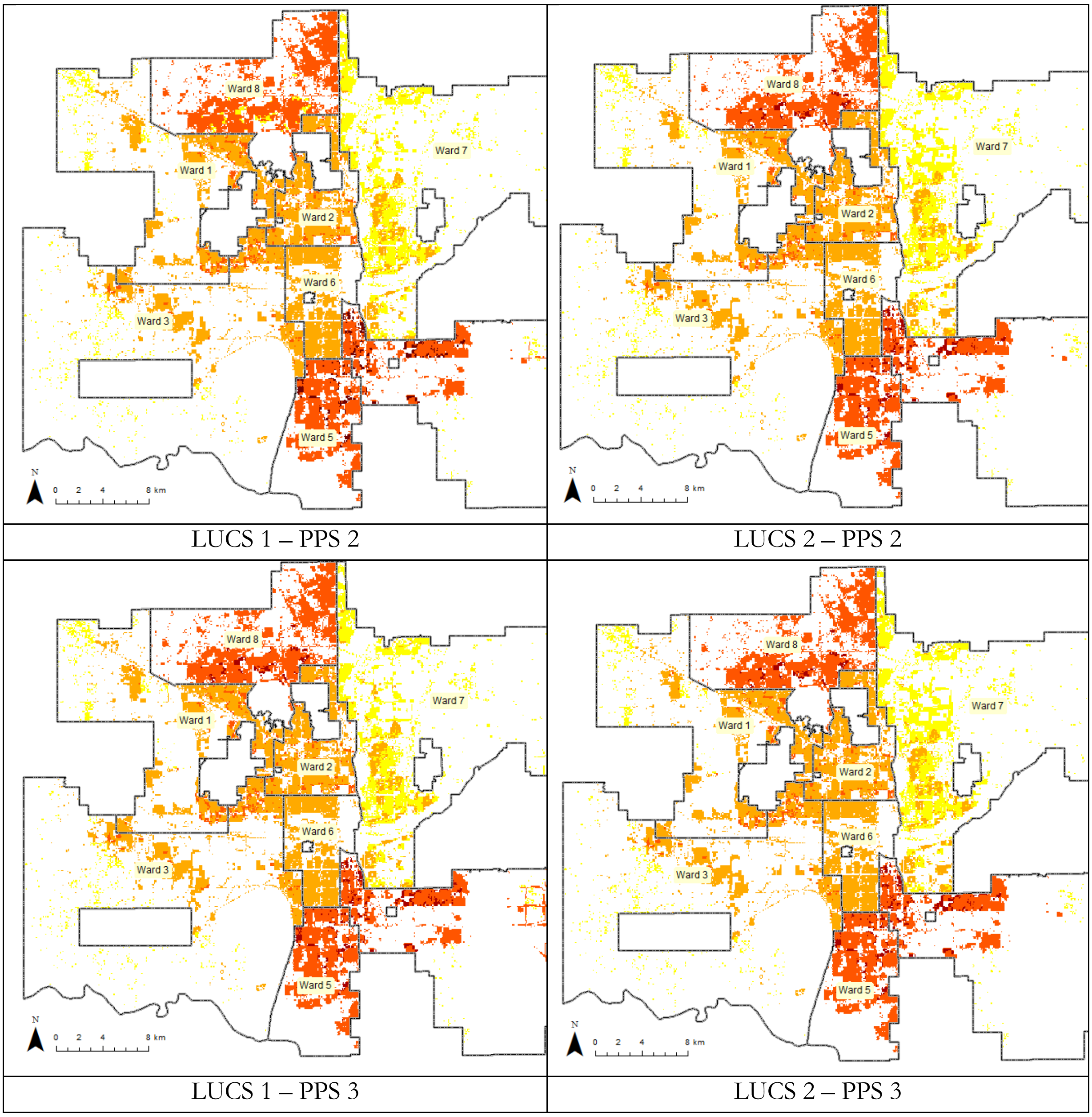
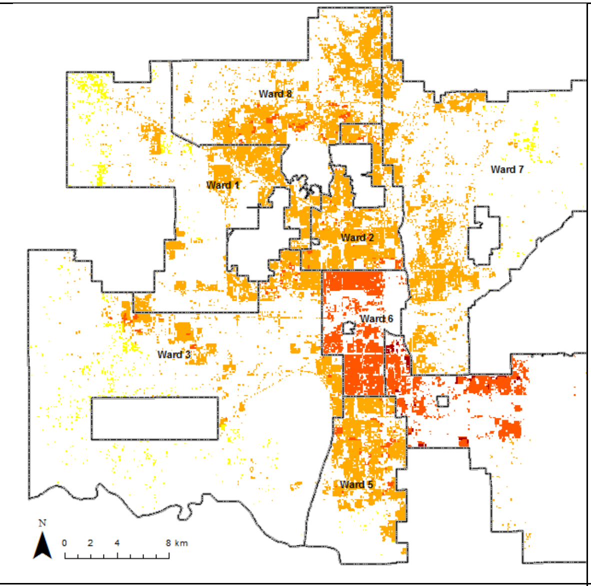


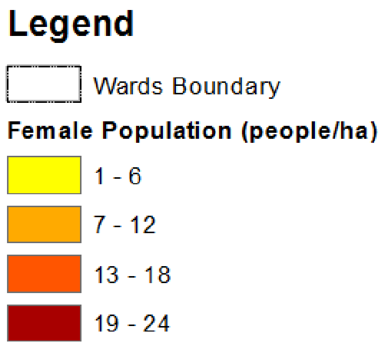
Figure 21 Elderly Population Urban Vulnerability Indicator

6.2.3. Female Population

The maps of the female population data for current (2010) and future condition (2030) in regards to the various simulation combination (as stated in Table 12) are presented in Figure 22. The disaggregated 100-m grid elderly population data resulted in the elderly population density with 4 classes: 1-6 people/ha, 7-12 people/ha, 13-18 people/ha and 19-24 people/ha. The maps show that compared to 2010 condition, the female population is increased in most of the area in ward 2,3,6 and 8 meanwhile the female population is decreased in ward 7 captured in all simulation combinations. This indicates that in 100-m grid level, different migration scenarios coupled with sprawl or compact urban development reveal a similar trend.



2010



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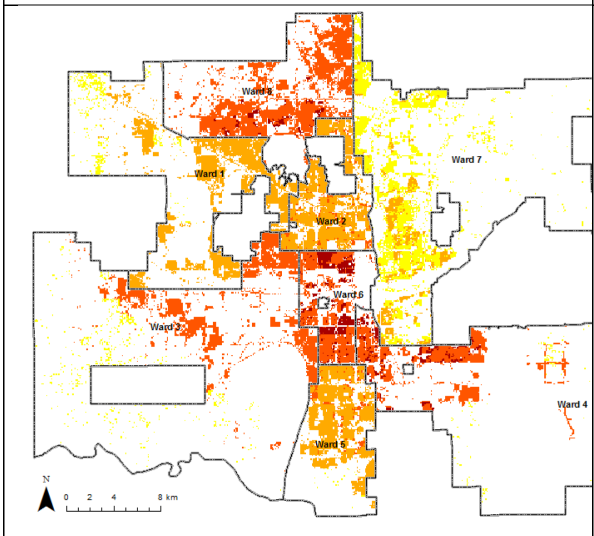
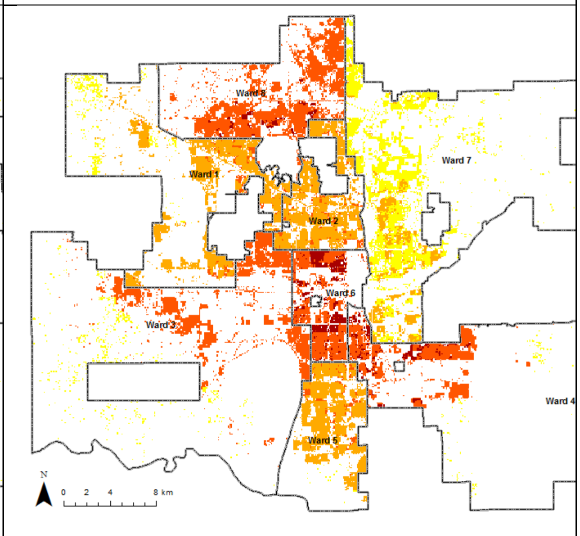
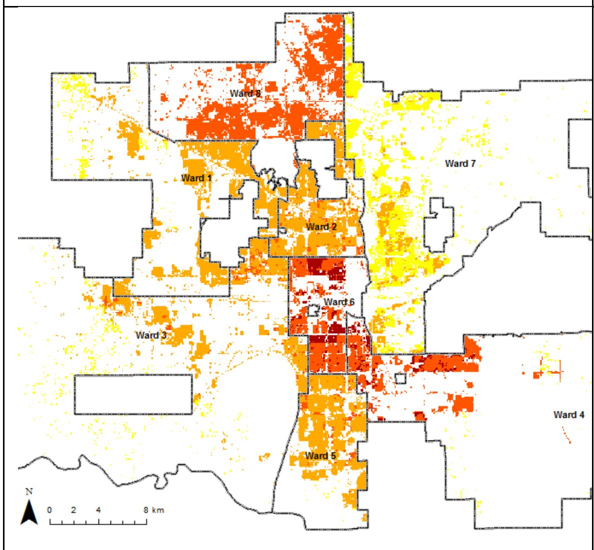


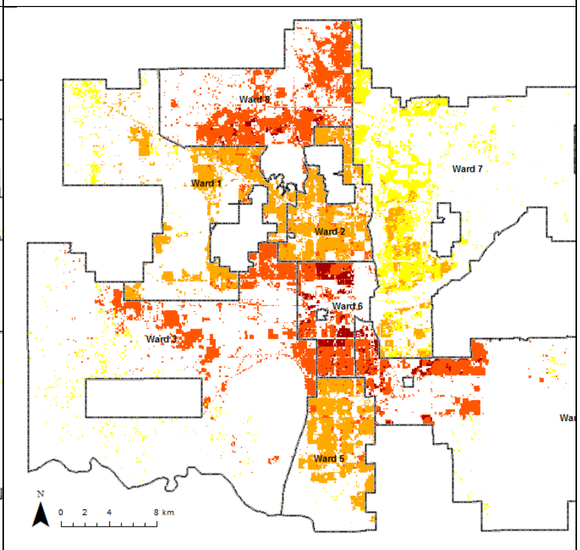
LUCS 1 – PPS 1



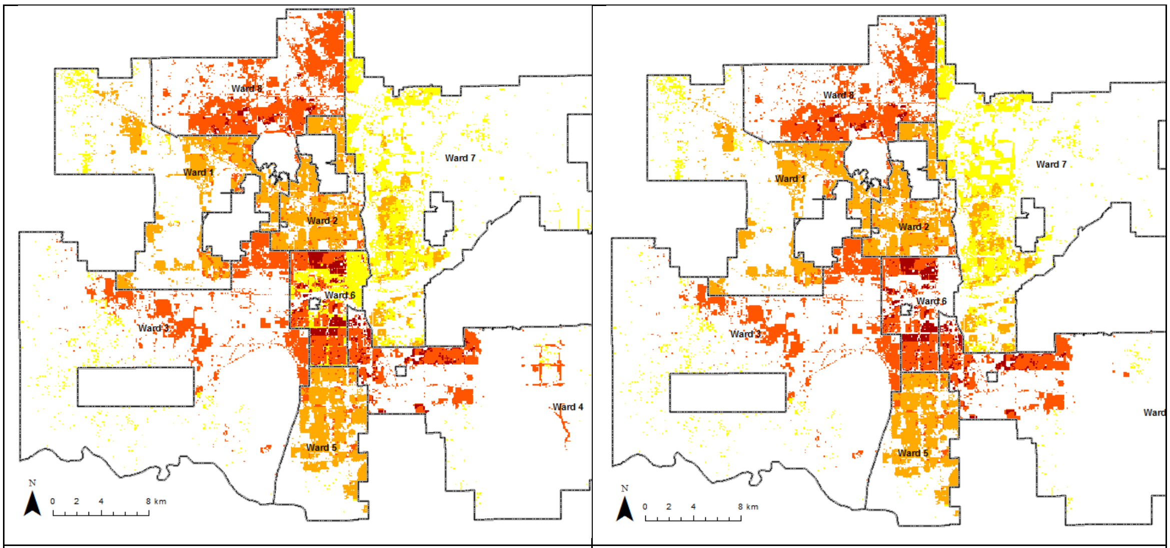
LUCS 2 – PPS 1



LUCS 1 – PPS 2



LUCS 2 – PPS 2



LUCS 1 – PPS 3 | LUCS 2 – PPS 3

Figure 22 Female Population Urban Vulnerability Indicator

6.3. Result

The index calculation resulted in a composite score with 0 – 1 scale. To map this result, the score was classified by using equal interval method into 5 classes: low (0 – 0.2), very low (0.21 – 0.4), medium (0,41 – 0.6), (0.61 – 0.8) high and very high (0.8 – 1). The profile of each index class is presented in Table 15. In addition, to simplify the discussion, the index calculation result is presented per LUC scenarios.

Table 15 Index Classification

Class	**Score**	**Population Density (people/ha)**	**Young Population (people/ha)**	**Elderly Population (people/ha)**	**Female Population (people/ha)**
Very Low	0 – 0.2	0 - 11	1	1	1 – 4
Low	0.21 – 0.4	11 – 27	1	2 – 4	6 – 10
Medium	0,41 – 0.6	29 – 37	2	2 – 6	7 – 11
High	0.61 – 0.8	31 – 38	2 – 4	3 – 7	15 – 20
Very High	0.8 – 1	41 – 46	2 – 4	4 – 7	16 – 22

The maps of the score classification for LUCS 1 simulation are shown in Figure 23.

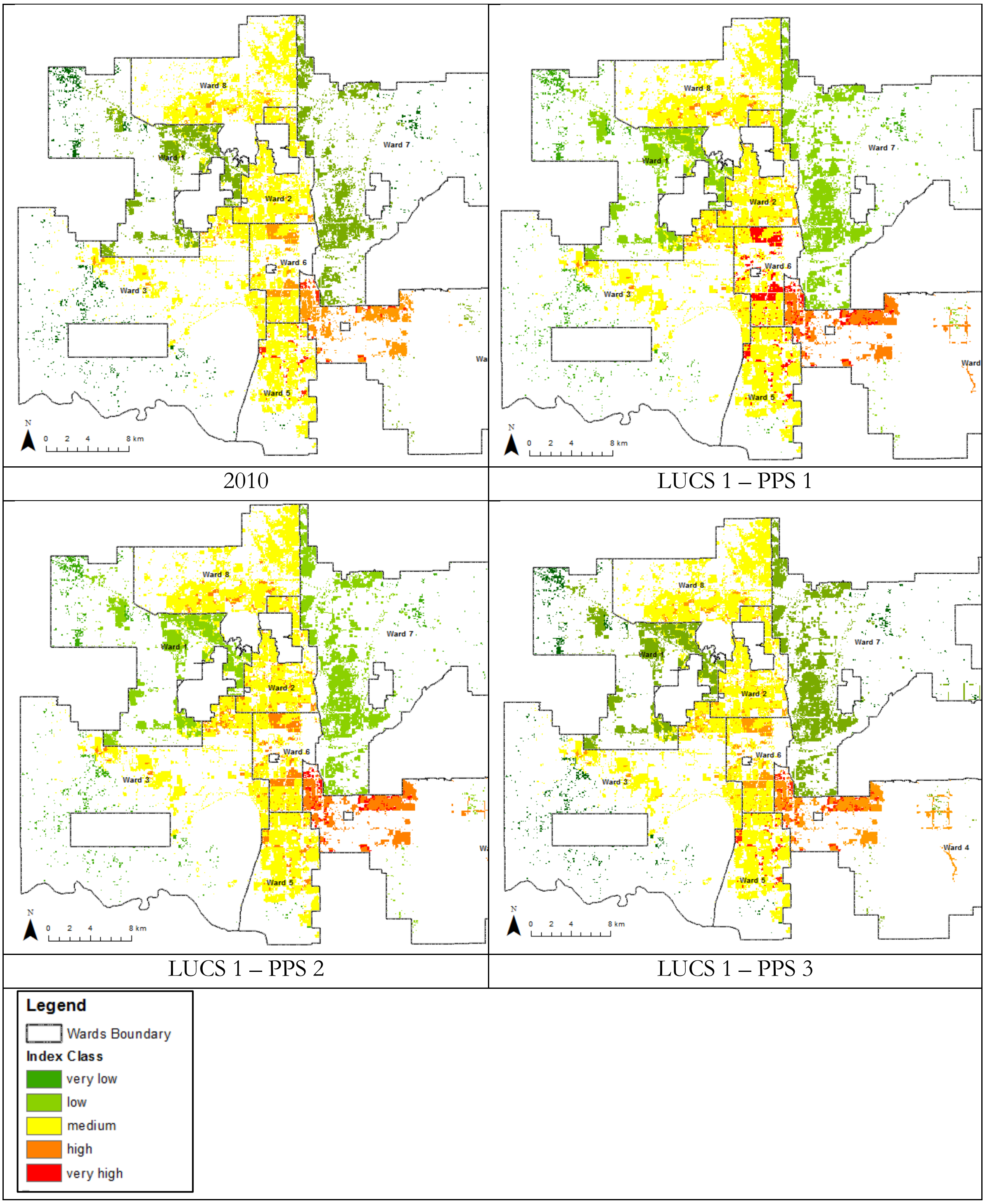


Figure 23 Index Calculation Map Result of Land Use Change Scenario 1

Based on the figure, there is a notable increase of several class index area. There is an increase of high class index located in ward 8. This increase is attributed to the increase of low density urban settlement. Meanwhile, it is observed that there is an increase of low class index in ward 7 area. The increase in this area is attributed to the increase of low and medium density urban settlement as predicted in the LUC model. Furthermore, there is also a changing of class index from high to very high class occurred in PPS 1 particularly in ward 6 but not in other simulation. Referring to the projected population composition in Table 7, this finding happened due to the effect of young population number. PPS 1 resulted in a higher number of young population among all of the population projection scenario for ward 6. As result, when this data incorporated in the index calculation, it gives a higher score so it is categorized in very high class.

The maps of the score classification for LUC scenario 1 simulation are shown in Figure 24.

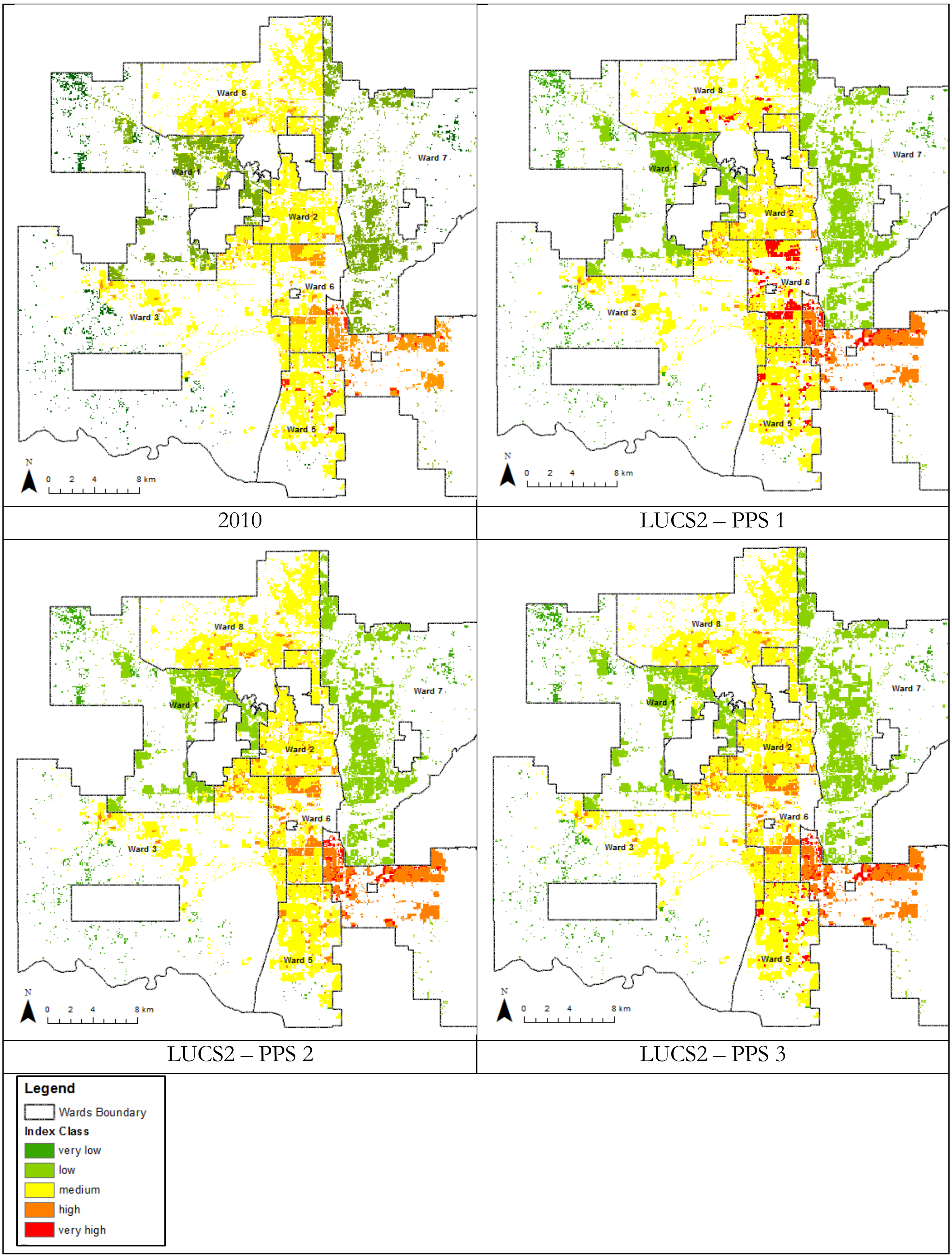
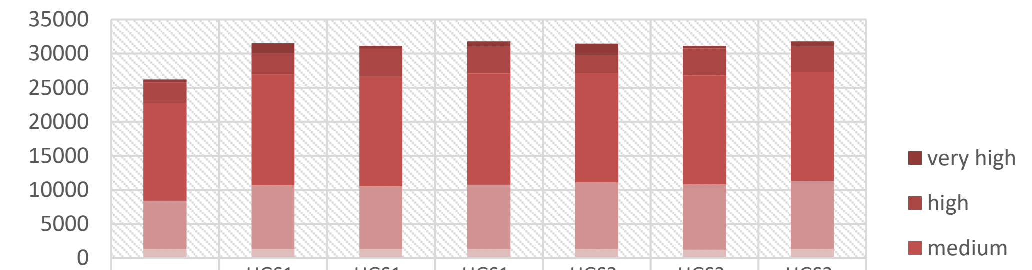


Figure 24 Index Calculation Map Result of Land Use Change Scenario 2

Based on the figure, it can be seen also that there is a notable increase of low class index concentrated on ward 7 area. The increase in this area is attributed to the increase of low and medium density urban settlement as predicted in the LUC model. This is in accordance to the result of the LUCS 2 simulation which resulted in a significant new urbanized area concentrated in ward 7. Furthermore, similar with the result of LUCS 1, it is also found that there is a changing of class index from high to very high class occurred in ward 6 and 8 in PPS 1 but not in other simulation combinations. This finding mostly attributed to the effect of the higher projected young population number within these wards resulted by PPS 1. As result, when this data incorporated in the index calculation, it gives a higher score so it is categorized in very high class.

To give a better overview regarding the future urban heat wave vulnerability, an aggregate area based on the vulnerable index classes was calculated and presented in Figure 25.



	2010	UGS1-PPS1	UGS1-PPS2	UGS1-PPS3	UGS2-PPS1	UGS2-PPS2	UGS2-PPS3
very high	404	1450	403	709	1683	389	683
high	3027	3109	4011	3973	2726	4003	3759
medium	14374	16300	16201	16339	15952	15930	16001
very low	7053	9306	9177	9440	9772	9595	9986
low	1341	1340	1340	1340	1340	1228	1340

Figure 25 Urban Heat wave Vulnerability Index Aggregated Area

In general, the graphs show that there is an increased area that possess very low to very high vulnerability. This condition occurred because there is a significant change of the exposed area due to the increase of settlement area in the future. It is captured from the estimation of high-resolution future population density that utilized the projected land use as basis map for the areal interpolation.

Next, the graph shows that vulnerability index in LUCS1 – PPS 1 and LUCS1 – PPS 2 produced the largest area with very high class. Referring to the visual observation of the maps in Figure 24, the existence of the very high vulnerability class in both simulation combinations can be found in ward 6. Looking back to the explanation regarding vulnerability indicator in current and future condition (in section 6.2), ward 6 is experiencing increased population density, elderly and female population. Furthermore, judging from all the vulnerability maps, ward 4 possesses a high and very high vulnerability class area which can be found in the 2010 and 2030 in all simulation combinations. Looking back at its vulnerability indicator, this ward also experiencing increased population density, elderly and female population. These findings indicate that ward 4 and 6 will be the most vulnerable ward in the future due to increased population density, elderly and female population. In addition, focusing on the existence of very high vulnerability class, the fact that LUCS2 – PPS 1 give the highest area of very high vulnerability indicates that compact development with the current population growth lead to the most vulnerable condition affecting particularly ward 4 and 6.

7. DISCUSSION

This chapter presents the discussion of the research findings. It starts with discussion about the population composition change projection followed by discussion about projection of the high-resolution population density. It continues with the reflection on the grid level vulnerability indicators as well as grid level vulnerability index calculation. Lastly, it ends with the discussion of findings regarding the future heat wave vulnerability of Oklahoma City.

7.1. Projecting population composition change in the future

The future population projection by age and gender makes it possible to derive the selected demographic data that matter for assessing urban vulnerability to heat wave. For this purpose, cohort-component method has performed well. The population projection conducted in ward level could reveal the changes of population composition in the ward level whereas the result can be aggregated to show the population and composition change in the city level.

Looking further to the population change component, the change of the population composition is highly sensitive to the migration in each age group. It seems that the increased or decreased population within each age group (induced by the migration) influence more the population composition change rather than the mortality and fertility components. Therefore, thorough study about migration focusing on the migration in each age group could be beneficial in getting insight about the population change in the future.

Migration is hard to predict and it is affected by many aspects such as economic and environment. Therefore, migration is the most volatile component of population change and it possesses the biggest uncertainty of population change. This study tries to address this uncertainty issue by incorporating population projection scenarios focused on different migration setting. In the city level and ward, the population projection shows that the scenarios applied were not giving significant difference of the total population count at the end. All three PPS showed an increasing trend (no extreme result) compared to the 2010 data whereas the population count difference among scenarios is relatively small. It seems that the migration scenarios employed in this study is not fully explored. This is due to the lack of resource and knowledge regarding the city's population growth trend and drivers. However, applying 10% difference for the current, decreased and increased migration (accounted for all population age groups) in the population projection scenario showed that slight difference of migration number assumption projects different population composition change in the future. Therefore, in regards to characterise the future demographic composition, the scenario development is essential. All in all, to what extend this scenario should be defined is depended on many factors such as the current development policies, stakeholders interests, policies in the broader scale, etc.

The most obvious effect revealed by employing different population projection scenario is that each scenario resulted different population composition in the future. Even though all PPS showed the same trend, they reveal different population composition both in the city level and ward level (in respect to each wards). By far, PPS 1 or the continuation of the current trend showed more vulnerability in all LUC scenario (captured in the area of ward 6). However, different assumption and scenarios employed would result different population composition in the future and it is necessary to build comprehensive migration scenario built from robust assumption. Thus, proper knowledge regarding the population characteristics and population growth trend and driver is essential.

Another point observation that can be pointed out regarding the population projection part is about the validation method. This study validated the population result by comparing the projected population in certain year (in this case it was year 2015) with the actual population count in the same year. This method is chosen simply because it is the common validation method used by demographers (i.e. Choi (2010)). However, there are many methods can be used to validate and assess the accuracy of the population projection result (such as face validity, plausibility, costs of production, timeliness, etc.) (Swanson & Tayman, 2012). Hence, how advance and detail the validation method used to assess the accuracy of the population projection depends of the purpose of the study, data availability, and stakeholder involved.

7.2. Projecting Future Population Density in High Resolution

The combination of population projection, land use model and population disaggregation method were proven able to produce future population density. There are two points that can be criticized regarding this process; the land use change model and the population disaggregation result.

Land use modelling

The developed GIS-based CA land use model has produced the future land use of Oklahoma City showing a future development trend of the city. The model incorporated the factors that drive the city's future development. These driving factors were selected by considering the city development trend combined with common factors that drives spatial development coming from the literatures. However, these driving factors are poorly formulated as they are not validated by stakeholders or thorough studies of land use change in Oklahoma City. However, for this study purpose, the selected driving factors are adequate as they can show the possibility of growth and land use change from different assumptions.

This study has produced the future land use of Oklahoma City under two possible development trajectories: sprawl and compact development scenarios. These scenarios showed different development pattern that might happen in the future. The scenarios employed in the land use change model are simplified to reflect the on-going development policy stated in the emerging land use plan. For this study purpose, these land use change scenarios are considered adequate to reflect the possibility of future land use as consequences of the emerging development policy in Oklahoma City. However, ideally, in regards to assessing future heat wave vulnerability in urban area, the model scenarios should be comprehensive to reflect all the possible development as the consequences from the on-going development policies. This is to give a better insight regarding the future physical development of the city that might influence the vulnerability in the following years.

Population Disaggregation Result

Dasymetric mapping has successfully aggregated the population data into 100-m grid level for current (2010) and future condition (2030). From this process, the results showed that there is an increased population density in certain wards captured in all simulation combination. The combination of different population projection scenarios and urban growth scenarios reflect the possibility of different population distribution in the future as the consequences of the uncertainty in population projection and the urban growth.

However, there is one notable finding revealed from the combination of urban and population projection. There is a mismatch between the increased population and the increased urbanized area. For instance, in LUCS1- PPS 1, ward 8 is projected will experience significant increased population but it is not accompanied by increased of urbanized area. This means that the population growth in ward level does not necessarily mean increased urbanized area. There are two points that caused this mismatch. First, there is a gap of analysis scale between the population projection and land use model. The population projection was calculated based on ward level meanwhile the land use change model was simulated in city level. As consequences, the land allocation is aggregated for the whole city but not according to wards. Simulating the land use model by dividing the land allocation per wards could be a solution to overcome this issue. Second, population projection and the land use change model have different driving factors. The population projection is influence by death, birth and migration meanwhile the land use change model is influenced by spatial feature such as proximity to downtown, existence of certain infrastructure or geographic phenomenon, land use zoning, etc.

7.3. Grid Level Vulnerability Variables

The elderly (65+ years), young (0-4 years) and female population are considered as the vulnerable groups to heat wave occurrence. The proportion of these vulnerable groups are used to quantify sensitivity of certain area in heat wave vulnerability assessment. The essence of this "population group proportion" in the heat wave vulnerability mapping is to show where these vulnerable groups "located and concentrated" so that the area with high proportion of these vulnerable groups is more sensitive to heat wave. To show this condition, the proportion of these vulnerable groups is calculated as percentage within certain administrative boundary (wards, district, block, etc.) in the common vulnerability mapping practice. The CC VA assessment method in this study follows the high-resolution VA which makes the analysis is done in grid level which has small area boundary (squared, 100m x 100m). Accordingly, the data used in the assessment should be transformed into this grid level.

In this study, as vulnerability indicators, the vulnerable groups are represented in a disaggregated population data resulted in vulnerable groups population density within 100-m grid. This is due to the reason that the total population in one grid/pixel is so small compared to the total population in ward or district level which makes using fraction (i.e. percentage, proportion) is not relevant to show the "concentration of vulnerable groups" in grid level. For example, the disaggregated data showed that there are 44 people in one grid with 100 m^2 size. Referring to this grid data, it is clearer to say there are "x number of female in this grid" rather than there are "z percent of female/young/elderly in this grid" as there are only few numbers of population there. Looking broader at the whole city context of this grid-level data, at the end it is more convenient to represent this data in terms of population density of female/young/elderly rather than percentage of female/young/elderly to express the concentration of the vulnerable groups in 100-m grid level. As consequences, the vulnerable groups population density is the vulnerability indicator used to quantify heat wave vulnerability (current and future condition) in this study. All in all, this finding reveals one of the main differences of conducting VA assessment using administrative boundary (choropleth map) (i.e. Bassil et al. (2010); Inostroza et al. (2016); Zhu et al. (2014)) with LU/LC (high resolution map) (i.e. Aubrecht et al. (2013); Freire & Aubrecht (2012); Morabito et al. (2015) and Tenerelli et al. (2015)). However, at the end, practitioners and researcher should map vulnerability at a resolution appropriate for the decision makers or stakeholders (de Sherbinin, 2014b)

7.4. Vulnerability Index Calculation in Grid Level

Furthermore, as vulnerability variables, even though the population density of female/young/elderly in high resolution is derived from the total population density, this does not make the vulnerability to heat wave is heavily dependent on the population density itself. High population density does not mean high population density of female/young/elderly as the percentage of female/young/elderly population in each ward also contribute to produce the female/young/elderly population density in the 100-m grid level.

The importance of the selected variables in measuring the vulnerability to heat wave depends on the weights of each variable (see Table 14). This concern brings another discussion regarding the determination of these weights. This study employed equal weight to calculate the composite index which comprises of sensitivity and exposure as the selected vulnerability components (both have 50% weight each). These components then broken down into its own vulnerability variable whereas the weights are also divided equally from the initial weight of the component. For instance, population density has 50% weight because it is the only vulnerability variable in the exposure component meanwhile population density of female, young and elderly weight 16.7% because there are 3 variables in sensitivity component (50% divided by 3=16.7%). With this weight allocation, practically, population density possesses the highest weight and the vulnerability index produced is influenced more by the population density rather than other selected vulnerability variables. With the limitation of knowledge regarding the study area, this weights allocation is considered appropriate as it avoids subjectivity and assumption without robust basic. At the end, in general, the weight allocation highly depends on the number of variables included in the VA and it depends also on the context of each area. This concern reflects to the importance of having more knowledge (documents, stakeholder involvement) to select the vulnerability variables as well as determining the weights of the vulnerability variables.

The vulnerability assessment approach demonstrated in this study has been proven able to produce detailed vulnerability map. The product of this VA approach can provide information regarding vulnerable area in a seamless manner, not bounded by certain administrative area. Hence, the output maps reveal detail variation of vulnerability area of the whole city. This output is beneficial for the policy maker to get a more advance understanding regarding the city's vulnerability to heat stress so that improved adaptation policy can be made. For instance, the detailed vulnerability map could be a useful input to see the coverage area and calculate how many people can be covered with a health care centre particularly in the area with high level of vulnerability index. This way, they could know how many people are covered and not covered, so this information could be a consideration whether they need to build a new health care centre or not including where they should put it in that highly vulnerable area. This is the main advantage of the vulnerability map produced by grid level VA approach as demonstrated in this study. However, one obvious shortcoming identified from this type of VA approach is that the result is rather difficult to interpret. This is mostly due to the reason that the output map is seamless and it is not associated with any spatial entity (wards, postcodes, blocks, district, etc). For instance, in this study we used the words such as "in the area of ward…" or "most of the area in wards…" to express the location of certain vulnerability index class. We cannot simply say that "this ward possesses high vulnerability class" to express the location of certain vulnerability index class as due to the detailed map, within a ward there maybe few vulnerability classes exist. This issue is also found when interpreting the vulnerability indicator in grid level. Another reason is that because the data is mapped in grid level, the changes of the vulnerability spatially cannot be seen vividly form the maps (unlike the VA map in choropleth map). Given these points, since it is hard to interpret, the result of the grid level VA is also hard to communicate. Thus, this is the biggest shortcoming identified from the grid level VA.

7.5. Future Heat Wave Vulnerability of Oklahoma City

There are several main findings regarding future heat wave vulnerability of Oklahoma City obtained from this study:

- The projected population in the city level showed that there will be more elderly population (65+years) meanwhile the young population (0-4 years old) are decreased indicating that the population of Oklahoma City is aging. Respectively, the projection in ward level shows similar trend of aging population. In addition, the population projection in city level showed increasing female population and this result is also captured in all wards.

- The land use modelling predicted that ward 7 and 4 will experience a significant increase of built up area particularly on medium and low development settlement area. This result is captured in all LUC scenario employed. This contributes to the increased of exposure area to heat wave in Oklahoma City.
- The estimated future population density showed that
- Referring to the vulnerability variables, from all simulations, this study predicts that there will be an increase of exposure in most of ward 3, 4, 6 and 7 area due to increased population density. It is also captured that the sensitivity will be increased particularly due to the increase of elderly and female population in most of ward 2,3,4, 6 and 8 area.
- All in all, the total vulnerability index maps show that there will be more exposure area to heat wave in the next 20 years particularly in ward 4 and 6 area in Oklahoma City. In the meantime, the result of the vulnerability index calculation shows that big portion of ward 4 and 6 area are the most vulnerable area in the next 20 years. This condition mostly driven by the increase of population density, elderly and female population within these wards.

These findings indicate that regarding the heat wave issue in Oklahoma City, the authority should pay attention more to ward 4 and 6. As captured from the spatial-temporal VA, these areas are having more exposure to heat wave because of the dense population compared to other areas (both in current and future condition). To add, these areas are also more sensitive to heat wave because of the vulnerable groups concentration (particularly elderly and female population) both in the present and future condition. This information is beneficial for the authority as input to evaluate their CC adaptation measures. For instance, using the output maps, the authority in Oklahoma City could evaluate their health care service in respect to the area covered as well as the number of people covered by the health care focusing on the vulnerable groups. This way could be one of the important input to enhance their health care service to cope with the vulnerability condition in the future.

7.6. Limitation

There are few limitations acknowledged in this study:

- First point is regarding the land use data. This study used the land use data in 2000 and 2010 derived from Landsat image using remote sensing technique. Even though the resulted land use maps are cross-checked with the existing land use data and land use zoning of Oklahoma City, the produced land use maps are considered are not representative enough. This is because the produced land use maps area not validated through ground check or consultation with the local authority. Moreover, the remote sensed 30-m grid Landsat data was found not adequate to capture the settlement area especially the rural settlement. This is due to the reason that the rural settlement is scarcely developed so it is hard to get the reflectance sample that is good enough to represent the rural settlement. As consequences, the produced land use maps are of low quality. Fortunately, the rural settlement is not of interest in the LU modelling as the model was designed to model the change of urban settlement based on the assumption that population increase is attributed to the urban settlement but not the rural settlement. Therefore, the fact that the rural settlement is not properly mapped does not affect the projection process. However, it still considered limitation as the poorly remote sensed rural settlement area is used in the dasymetric mapping process and it reduced the quality of the produced disaggregated population data.
- Another notable limitation of this study is regarding the stakeholder involvement. This point has been mentioned in discussion parts, particularly regarding population projection scenario, land use

change scenario, vulnerability variable selection and vulnerability weight definition. Stakeholder involvement is considered as essential part that is missing as it could be beneficial in providing information regarding these essential parts of the study. Consultation with the local stakeholder would enhance the study by providing more information that can be used to develop better population projection and land use scenarios, select a more thorough vulnerability variables and provide more contextual vulnerability variables weight. In general, consultation with the local stakeholder would also beneficial in giving deeper understanding about the heat wave issues in the study area. This information would be helpful as input in delivering a more comprehensive urban heat related vulnerability study.

8. CONCLUSION AND RECOMMENDATION

8.1. Conclusion

This study has fulfilled the main objective of developing an approach to incorporate demographic changes in assessing future urban vulnerability to heat stress. This is supported by the fulfilment of the specific objectives of this study.

First, a research framework that ties the knot between demographic data, heat wave vulnerability determinants and urban vulnerability framework was. This framework served as the conceptual basis to identify the required demographic data for future urban heat wave vulnerability. As the conclusion of the first research objective, the framework showed that population density, female population, young population (0 – 4 years old), elderly population (65+ year) and population by ethnicities are the common demographic data used to measure heat wave vulnerability in urban area.

Meanwhile, as the conclusion of the second research objective, the future vulnerability assessment in urban context requires projection of the selected demographic data in intra urban scale (100-m grid was chosen as the unit of analysis). Therefore, population projection by means of cohort component method was used to project the future population composition (attributed to the future number of female population, young population, elderly population) meanwhile combination of population projection (cohort component method), land use modelling (GIS-Based CA Model) and population disaggregation (dasymetric mapping) were used to estimate the future population density.

Next, the proposed methods successfully provide the required data to conduct future urban heat wave vulnerability in high resolution. After incorporated in the vulnerability index calculation (current and future condition), the demographic changes captured by the proposed methods give difference to the future vulnerability condition in terms of increased vulnerability area and changed vulnerability class. This is the conclusion of the third research objective.

In addition, as the novelty of the research, combination of population projection, dasymetric mapping and land use change model has successfully captured the spatial – temporal demographic change in the future vulnerability assessment. These methods are not new and already well developed. This implicates that it is possible to use a combination of various methods and approach to address climate change issues particularly in the area of future vulnerability assessment.

Overall, this study reveal the importance of incorporating that that demographic changes will lead to different vulnerability condition in the future. The change of population composition contributes in giving insight about the future sensitivity as it shows the changes of vulnerable group population numbers. Meanwhile, the projected population density that might happen under various urban development scenario and population projection scenarios show that the exposure to heat wave will increase in terms of quantity and area extent in the future. All in all, this information provides a meaningful insight regarding vulnerable areas in the future including its demographic drivers, thus supporting authority and policy maker to deliver better CC adaptation measures.

8.2. Recommendation for Future Studies

This study explores the possibility of combining existing and developed methods to address the issues identified regarding the future vulnerability assessment. However, further studies are required to the test usage of proposed methods in different settings and to improve the concept or operability of the concept.

One possible recommendation is to test the usage of the proposed method in different type of cities. Cities in developing countries possesses more threat to climate change impact due to lack of resource, overly dense and populated area, and many other problems faced by those cities. This condition superimposed with the more severe climate change impact the future, raise a need to characterize the future vulnerability to formulate better climate change adaptation policy. Thus, it is worthy to try the usage of this study approach in developing countries setting.

Furthermore, exploring different scenarios regarding population growth or land use change trend also valued as a worthy further research avenue. For example, using extreme population change scenario (supported with robust assumption and background), decreasing population or shrinking cities might be interesting to be use as scenarios to be explored further study.

It is also important to test the effect of methodological variation in operating the proposed approach. For instance, using more advance population projection method, using more complex land use model and using another type of population disaggregation. This way could enhance and improve the proposed method by finding the most convenient and efficient methods combined or it could also reveal more the shortcomings and benefit of the proposed method leading to a different ideas and approach in addressing the future vulnerability assessment issues.

Regarding future vulnerability assessment in local scale such as urban area, it is necessary to investigate the usage of the SSPs and see the difference with the scenario developed from the local context. The SSPs are formulated from the global scale whereas the assumptions used are different with the real condition in the local scale. Regarding this mismatch, one can compare which one is more useful in regards to addressing CC future in the future. It could be useful also to evaluate the SSPs by reflecting it with the scenario from local context. However, there are many areas of interest can be explored within this view and it is worthy as a further research direction in CC future vulnerability studies.

Moreover, reflecting to the vulnerability by (Romero-Lankao et al., 2012), it is necessary to address the possible future changes within the exposure, sensitivity, adaptive capacity and hazard. The first two have been addressed in this study. What is needed is to conduct a complete future vulnerability assessment by incorporating changes that might happen in regards to all vulnerability component. This emerge as a potential future study direction in CC studies.

All in all, demographic changes clearly influence the vulnerability in upcoming years. Referring to elements of socioeconomic characteristics as reported in the IPCC AR4 (2007), it is suggested to investigate the changes in other elements such as economic, natural resource use, governance and policy, and cultural and to see how the changes of these element could affect CC future vulnerability. Research in this perspective are still lacking and it is important to foreseen these changes to deal with CC in the future.

LIST OF REFERENCES

Amengual, A., Homar, V., Romero, R., Brooks, H. E., Ramis, C., Gordaliza, M., & Alonso, S. (2014). Projections of heat waves with high impact on human health in Europe. *Global and Planetary Change*, *119*, 71–84. http://doi.org/10.1016/j.gloplacha.2014.05.006

Aubrecht, C. (2012). The contribution of multi-level geospatial information to assessing urban social vulnerability to earthquakes, (August 2016).

Aubrecht, C., & Özceylan, D. (2013a). Identification of heat risk patterns in the U.S. National Capital Region by integrating heat stress and related vulnerability. *Environment International*, *56*, 65–77. http://doi.org/10.1016/j.envint.2013.03.005

Aubrecht, C., & Özceylan, D. (2013b). Identification of heat risk patterns in the U.S. National Capital Region by integrating heat stress and related vulnerability. *Environment International*, *56*, 65–77. http://doi.org/10.1016/j.envint.2013.03.005

Aubrecht, C., Steinnocher, K., Kostl, M., Zuger, J., & Loibl, W. (2013). Long-term spatio-temporal social vulnerability variation considering health-related climate change parameters particularly affecting elderly. *Natural Hazards*, *68*(3), 1371–1384. http://doi.org/10.1007/s11069-012-0324-0

Bao, J., Li, X., & Yu, C. (2015, June 26). The construction and validation of the heat vulnerability index, a review. *International Journal of Environmental Research and Public Health*. http://doi.org/10.3390/ijerph120707220

Barker, S. (2012). *2012 Demographic State of The State Report: Oklahoa State and County Population Projections through 2075*. Oklahoma City.

Basara, J. B., Basara, H. G., Illston, B. G., & Crawford, K. C. (2010). The Impact of the Urban Heat Island during an Intense Heat Wave in Oklahoma City. *Advances in Meteorology*, *DOI:10.115*, 1–11. http://doi.org/10.1155/2010/230365

Bassil, K., Rinner, C., & Patychuk, D. (2010). Validating the Toronto Spatial Heat Vulnerability Assessment : Research Findings & Proposed Methods, (December), 1–26.

Batty, M., & Xie, Y. (1997). Possible urban automata. *Environment and Planning B: Planning and Design*, *24*(2), 175–192. http://doi.org/10.1068/b240175

Baum-Snow, N. (2006). *Did Highways Cause Suburbanization?*

Birkin, M., & Clarke, M. (2011). Spatial Microsimulation Models: A Review and a Glimpse into the Future. In *Population Dynamics and Projection Methods, Understanding Population Trends and Processes* (pp. 193–208). http://doi.org/10.1007/978-90-481-8930-4

BLS. (2012). Employed persons by detailed industry and age. Retrieved February 21, 2017, from https://www.bls.gov/cps/cpsaat18b.htm

Blum, L. N., Bresolin, L. B., & Williams, M. a. (1998). Heat-related illness during extreme weather emergencies. *Journal of the American Medical Association*, *279*(19), 1514. http://doi.org/10.1001/jama.279.19.1514

Bradford, K., Abrahams, L., Hegglin, M., & Klima, K. (2015). A Heat Vulnerability Index and Adaptation Solutions for Pittsburgh, Pennsylvania. *Environmental Science and Technology*, *49*(19), 11303–11311. http://doi.org/10.1021/acs.est.5b03127

Burchfield, M., Overman, H. G., Puga, D., & Turner, M. A. (n.d.). CAUSES OF SPRAWL: A PORTRAIT FROM SPACE*.

Cantergiani, C., & Delgado, M. G. (2016). Design of an Agent-Based Model to Simulate Urban Growth at Corredor Del Henares (Region of Madrid). *Boletín de La Asociación de Geógrafos Españoles*.

Choi, S. (2010). Application of the Cohort Component Model to Development of Local Population Projections. *The 51st Association of Collegiate Schools of Planning Conference*, 22. Retrieved from http://www.scag.ca.gov/Documents/acsp10_localcohort100710.pdf

Chow, W. T. L., Chuang, W.-C., & Gober, P. (2012). Vulnerability to extreme heat in metropolitan Phoenix: spatial, temporal, and demographic dimensions. *The Professional Geographer*, *64*(2), 286–302. http://doi.org/10.1080/00330124.2011.600225

Costa-Font, J., Wittenberg, R., Concepció, A., Ae, P., Comas-Herrera, A., Gori, C., … Rothgang, H. (2008). Projecting Long-Term Care Expenditure in Four European Union Member States: The Influence of Demographic Scenarios. *Soc Indic Res*, *86*, 303–321. http://doi.org/10.1007/s11205-007-9140-4

Couclelis, H. (1997). From cellular automata to urban models: new principles for model development and implementation. *Environment and Planning B: Planning and Design*, *24*(2), 165–174. http://doi.org/10.1068/b240165

D'Ippoliti, D., Michelozzi, P., Marino, C., De'Donato, F., Menne, B., Katsouyanni, K., … Perucci, C. A. (2010). The impact of heat waves on mortality in 9 European cities: results from the EuroHEAT project. *Environmental Health : A Global Access Science Source*, *9*(1), 37. http://doi.org/10.1186/1476-069X-9-37

Danks, D. M., Webb, D. W., & Allen, J. (1962). Heat illness in infants and young children: A study of 47 cases. *British Medical Journal*, *2*, 287–293. http://doi.org/10.1136/bmj.2.5300.287

Deadman, P., Brown, R. D., & Gimblett, H. R. (1993). Modelling Rural Residential Settlement Patterns with Cellular Automata. *Journal of Environmental Management*. http://doi.org/Cited By (since 1996) 44\rExport Date 26 November 2011

de Sherbinin, A. M. (2014a). *Mapping the unmeasurable? Spatial Analysis of Vulnerability to Climate Change and Climate Variability*. http://doi.org/10.3990/1.9789036538091

de Sherbinin, A. M. (2014b). *Spatial Climate Change Vulnerability Assessments : a Review of Data , Methods , and Issues*.

Ding, D., Bennett, D., & Secchi, S. (2015). Investigating Impacts of Alternative Crop Market Scenarios on Land Use Change with an Agent-Based Model. *Land*, *4*(4), 1110–1137. http://doi.org/10.3390/land4041110

Duranton, G., & Puga, D. (2014). The Growth of Cities. *Handbook of Economic Growth*, *2*, 781–853. http://doi.org/10.1016/B978-0-444-53540-5.00005-7

Ebi, K. L., Teisberg, T. J., Kalkstein, L. S., Robinson, L., & Weiher, R. F. (2004). Heat watch/warning systems save lives: Estimated costs and benefits for Philadelphia 1995-98. *Bulletin of the American Meteorological Society*, *85*(8), 1067–1073. http://doi.org/10.1175/BAMS-85-8-1067

ECONorthwest. (2014). *Oklahoma City 2050 Growth Scenarios: Cost Analysis*. Oklahoma.

Eicher, C. L., & Brewer, C. A. (2001). Dasymetric Mapping and Areal Interpolation: Implementation and Evaluation. *Cartography and Geographic Information Science*, *28*(2), 125–138. http://doi.org/10.1559/152304001782173727

Field, A. (2009). *Discovering Statistics Using SPSS* (3rd ed.). Sage. http://doi.org/10.1111/insr.12011_21

Freire, S., & Aubrecht, C. (2012). Integrating population dynamics into mapping human exposure to seismic hazard. *Natural Hazards and Earth System Science*, *12*(11), 3533–3543. http://doi.org/10.5194/nhess-12-3533-2012

Fussel, H. M., & Klein, R. J. T. (2006). Climate change vulnerability assessments: An evolution of conceptual thinking. *Climatic Change*, *75*(3), 301–329. http://doi.org/10.1007/s10584-006-0329-3

Gallego, F. J., Batista, F., Rocha, C., & Mubareka, S. (2011). Disaggregating population density of the European Union with CORINE land cover. *International Journal of Geographical Information Science*, *25*(12), 2051–2069. http://doi.org/10.1080/13658816.2011.583653

George, M. V., Smith, S. K., Swanson, D. A., & Tayman, J. (2004). Population Projections. In J. Siegel & D. Swanson (Eds.), *The Methods and Materials of Demography*. San Diego: Elsevier Academic Press. Retrieved from https://www.bebr.ufl.edu/sites/default/files/Research Reports/2004_m_m_projections_.pdf

GIZ, & CCA RAI. (2014). *A Framework for Climate Change Vulnerability Assessments*. (S. Satapathy, I. Porsché, D. Rolker, S. Bhatt, S. Tomar, & S. Nair, Eds.). New Delhi: GIZ, CCA RAI. Retrieved from https://www.weadapt.org/sites/weadapt.org/files/legacy-new/knowledge-base/files/5476022698f9agiz2014-1733en-framework-climate-change.pdf

Gottlieb, P. (1995). Residential Amenities, Firm Location and Economic Development. *Urban Studies*, *32*(9), 1413–1436. http://doi.org/10.1080/00420989550012320

Hahn, M. B., Riederer, A. M., & Foster, S. O. (2009). The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change-A case study in Mozambique. *Global Environmental Change*, *19*(1), 74–88. http://doi.org/10.1016/j.gloenvcha.2008.11.002

Harlan, S. L., Brazel, A. J., Prashad, L., Stefanov, W. L., & Larsen, L. (2006). Neighborhood microclimates and vulnerability to heat stress. *Social Science & Medicine*, *63*, 2847–2863. http://doi.org/10.1016/j.socscimed.2006.07.030

Hauser, P. M., and Duncan, O. D. (U. of C. P. (1959). *The Study of Population: An Inventory and Appraisal*. Chicago: University of Chicago Press.

Heaviside, C., Tsangari, H., Paschalidou, A., Vardoulakis, S., Kassomenos, P., Georgiou, K. E., & Yamasaki, E. N. (2016). Heat-related mortality in Cyprus for current and future climate scenarios. *Science of the Total Environment, The*, *569–570*, 627–633. http://doi.org/10.1016/j.scitotenv.2016.06.138

Hinkel, J. (2011). " Indicators of vulnerability and adaptive capacity": Towards a clarification of the science-policy interface. *Global Environmental Change*, *21*(1), 198–208. http://doi.org/10.1016/j.gloenvcha.2010.08.002

Huang, C., Barnett, A. G., Wang, X., Vaneckova, P., Fitzgerald, G., & Tong, S. (2011). Projecting Future heat-related mortality under climate change scenarios: A systematic review. *Environmental Health Perspectives*, *119*(12), 1681–1690. http://doi.org/10.1289/ehp.1103456

Imhoff, E. Van, & Post, W. (2008). Microsimulation Methods for Population Projection. *Population: An English Selection*, *10*(1), 97–138. Retrieved from http://www.persee.fr/doc/pop_0032-4663_1998_hos_10_1_6824

Inostroza, L., Palme, M., & de la Barrera, F. (2016). A Heat Vulnerability Index: Spatial Patterns of Exposure, Sensitivity and Adaptive Capacity for Santiago de Chile. *Plos One*, *11*(9), e0162464. http://doi.org/10.1371/journal.pone.0162464

IPCC. (2001). CLIMATE CHANGE 2001 : impacts , adaptation and vulnerability. *Working Group II Impacts Adaptation and Vulnerability*, *22*(10), 10. http://doi.org/10.1002/joc.775

IPCC. (2007a). *Climate Change 2007: impacts, adaptation and vulnerability: contribution of Working Group II to the fourth assessment report of the Intergovernmental Panel. M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson*. Cambridge. Retrieved from http://books.google.com/books?hl=en&lr=&id=TNo-SeGpn7wC&oi=fnd&pg=PA81&dq=Climate+Change+2007:+Impacts,+Adaptation+and+Vulnerability.+Contribution+of+Working+Group+II+to+the+Fourth+Assessment+Report+of+the+Intergovernmental+Panel+on+Climate+Change&ots=vP2

IPCC. (2007b). *Climate Change 2007 Synthesis Report. Intergovernmental Panel on Climate Change [Core Writing Team IPCC*. Retrieved from http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr_full_report.pdf

IPCC. (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation*. ([Field; C.B.; V. Barros; T.F. Stocker; D. Qin; D.J. Dokken; K.L. Ebi; M.D. Mastrandrea; K.J.; Mach; G.-K. Plattner; S.K. Allen; M. Tignor; and P.M. Midgley (eds.), Ed.). Cambridge: Cambridge University Press.

IPCC. (2013). Summary for Policymakers. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 33. http://doi.org/10.1017/CBO9781107415324

IPCC. (2014). Climate Change 2014 Synthesis Report Summary Chapter for Policymakers. *Ipcc*, 31.

http://doi.org/10.1017/CBO9781107415324

Irwin, E. G., & Geoghegan, J. (2001). Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems and Environment*, *85*, 7–23.

Ishigami, A., Hajat, S., Kovats, R. S., Bisanti, L., Rognoni, M., Russo, A., & Paldy, A. (2008). An ecological time-series study of heat-related mortality in three European cities. *Environmental Health : A Global Access Science Source*, *7*, 5. http://doi.org/10.1186/1476-069X-7-5

Itami, R. (1994). Simulating spatial dynamics: cellular automata theory. *Landscape and Urban Planning*, *30*(94), 27–47. http://doi.org/10.1016/0169-2046(94)90065-5

Johnson, D. P., Stanforth, A., Lulla, V., & Luber, G. (2012). Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. *Applied Geography*, *35*(1–2), 23–31. http://doi.org/10.1016/j.apgeog.2012.04.006

Johnson, D. P., & Wilson, J. S. (2009). The socio-spatial dynamics of extreme urban heat events: The case of heat-related deaths in Philadelphia. *Applied Geography*, *29*(3), 419–434. http://doi.org/10.1016/j.apgeog.2008.11.004

Johnson, D. P., Wilson, J. S., & Luber, G. C. (2009). Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *International Journal of Health Geographics*, *8*(1), 57. http://doi.org/10.1186/1476-072X-8-57

KC, S., & Lutz, W. (2014). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*. http://doi.org/10.1016/j.gloenvcha.2014.06.004

Koomen, E., Stillwell, J., Bakema, A., & Scholten, H. J. (2007). *Modelling Land-Use Change: Progress and Applications*. *GeoJournal* (Vol. 90). http://doi.org/10.1007/978-1-4020-5648-2

Kovats, R. S., & Hajat, S. (2008). Heat Stress and Public Health: A Critical Review. *Annu. Rev. Public Health*, *29*(9), 1–9. http://doi.org/10.1146/annurev.publhealth.29.020907.090843

Kumar, P., Geneletti, D., & Nagendra, H. (2016). Spatial assessment of climate change vulnerability at city scale: A study in Bangalore, India. *Land Use Policy*, *58*, 514–532. http://doi.org/10.1016/j.landusepol.2016.08.018

Lemonsu, A., Viguié, V., Daniel, M., & Masson, V. (2015). Vulnerability to heat waves: Impact of urban expansion scenarios on urban heat island and heat stress in Paris (France). *Urban Climate*, *14*, 586–605. http://doi.org/10.1016/j.uclim.2015.10.007

Lewis, K., & Burd-Sharps, S. (2014). American Human Development Report: The Measure of America 2013 – 2014. Retrieved from www.measureofamerica.org/measure_of_america2013-2014

Li, X., & Yeh, A. G.-O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science*, *14*(2), 131–152. http://doi.org/10.1080/136588100240886

Loughnan, M., Nicholls, N., & Tapper, N. J. (2012). Mapping Heat Health Risks in Urban Areas. *International Journal of Population Research*, *2012*, 1–12. http://doi.org/10.1155/2012/518687

Lutz, W., & Muttarak, R. (2017). Forecasting societies' adaptive capacities through a demographic metabolism model. *Nature Climate Change*, *7*(3), 177–184. http://doi.org/10.1038/nclimate3222

Malone, E. L., & La Rovere, E. L. (2005). Assessing Current and Changing Socio-Economic Conditions. In *Adaptation Policy Frameworks for Climate Change: Developing Strategies, Strategies, Policies and Measures* (pp. 145–163). Cambridge and New York: Cambridge University Press.

Medina-Ramón, M., & Schwartz, J. (2007). Temperature, temperature extremes, and mortality: a study of acclimatisation and effect modification in 50 US cities. *Occup Environ Med*, *64*, 827–833. http://doi.org/10.1136/oem.2007.033175

Medina-Ramón, M., Zanobetti, A., Cavanagh, D. P., & Schwartz, J. (2006). Extreme temperatures and mortality: Assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. *Environmental Health Perspectives*, *114*(9), 1331–1336.

http://doi.org/10.1289/ehp.9074

Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science*, *305*(5686), 994–997. http://doi.org/10.1126/science.1098704

Melillo, J. M., Richmond, T. C., Yohe, G. W., & US National Climate Assessment. (2014). *Climate change impacts in the United States: the third national climate assessment. US Global change research program* (Vol. 841). http://doi.org/10.7930/j0z31WJ2

Mennis, J. (2003). Generating Surface Models of Population Using Dasymetric Mapping*. *The Professional Geographer*, *55*(August 2002), 31–42. http://doi.org/10.1111/0033-0124.10042

Mennis, J. (2009). Dasymetric mapping for estimating population in small areas. *Geography Compass*, *3*(2), 727–745. http://doi.org/10.1111/j.1749-8198.2009.00220.x

Michelozzi, P., De Sario, M., Accetta, G., De'Donato, F., Kirchmayer, U., D'Ovidio, M., & Perucci, C. A. (2006). Temperature and summer mortality: geographical and temporal variations in four Italian cities. *Journal of Epidemiology and Community Health*, *60*, 417–423. http://doi.org/10.1136/jech.2005.040857

Morabito, M., Crisci, A., Gioli, B., Gualtieri, G., Toscano, P., Di Stefano, V., … Gensini, G. F. (2015). Urban-hazard risk analysis: Mapping of heat-related risks in the elderly in major Italian cities. *PLoS ONE*, *10*(5), 1–18. http://doi.org/10.1371/journal.pone.0127277

National Weather Service. (2016). National Weather Service Climate Summaries. Retrieved February 20, 2017, from http://w2.weather.gov/climate/xmacis.php?wfo=ohx

Nelson, J. (2004). Mapping Population Density : Integrating census data and land cover. *The Geographical Review*, 900.

Nelson, K. S., Abkowitz, M. D., & Camp, J. V. (2015). A method for creating high resolution maps of social vulnerability in the context of environmental hazards. *Applied Geography*, *63*, 89–100. http://doi.org/10.1016/j.apgeog.2015.06.011

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., … Solecki, W. (2014). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*. http://doi.org/10.1016/j.gloenvcha.2015.01.004

Oklahoma Department of Libraries. (2016). *Oklahoma Economic Indicators*.

Peña, E. N. (2012). *Using Census Data, Urban Land-Cover Classification, and Dasymetric Mapping to Measure Urban Growth of The Lower Rio Grande Valley, Texas*. California.

Penticton, C. of. (2015). Future Land Use Map.

Petkova, E. P., Vink, J. K., Horton, R. M., Gasparrini, A., Bader, D. A., Francis, J. D., & Kinney, P. L. (2016). Towards More Comprehensive Projections of Urban Heat-Related Mortality: Estimates for New York City under Multiple Population, Adaptation, and Climate Scenarios. *Environmental Health Perspectives*, (January). http://doi.org/10.1289/EHP166

Prastacos, P., Chrysoulakis, N., & Kochilakis, G. (2011). Urban Atlas, land use modelling and spatial metric techniques. In *ERSA conference papers*.

Rayer, S. (2015). Demographic Techniques: Small-area Estimates and Projections, *6*, 162–169. http://doi.org/10.1016/B978-0-08-097086

Reibel, M., & Agrawal, A. (2007). Areal interpolation of population counts using pre-classified land cover data. *Population Research and Policy Review*, *26*(5–6), 619–633. http://doi.org/10.1007/s11113-007-9050-9

Reid, C. E., O'Neill, M. S., Gronlund, C. J., Brines, S. J., Brown, D. G., Diez-Roux, A. V., & Schwartz, J. (2009). Mapping community determinants of heat vulnerability. *Environmental Health Perspectives*, *117*(11), 1730–1736. http://doi.org/10.1289/ehp.0900683

Roback, J. (1982). Wages , Rents , and the Quality of Life. *The Journal of Political Economy*, *90*(6), 1257–1278. http://doi.org/10.1086/261120

Romero-Lankao, P., Qin, H., & Dickinson, K. (2012). Urban vulnerability to temperature-related hazards: A meta-analysis and meta-knowledge approach. *Global Environmental Change*, *22*(3), 670–683. http://doi.org/10.1016/j.gloenvcha.2012.04.002

Rotmans, J., & van Asselt, M. B. A. (2001). Uncertainty management in integrated assessment modeling: Towards a pluralistic approach. *Environmental Monitoring and Assessment*, *69*(2), 101–130. http://doi.org/10.1023/A:1010722120729

Ruben, R., Moll, H., & Kuyvenhoven, A. (1998). Integrating Agricultural Research and Policy Analysis: Analytical Framework and Policy Applications for Bio-economic Modelling. *Agricultural Systems*, *58*(3), 331–349.

S. Rosen. (1979). Wage-Based Indexes of Urban Quality of Life. In *Current Issues in Urban Economics* (pp. 74–104). Baltimore: Johns Hopkins University Press.

Schwartz, J. (2005). Who is sensitive to extremes of temperature?: A case-only analysis. *Epidemiology (Cambridge, Mass.)*, *16*(1), 67–72. http://doi.org/10.1097/01.ede.0000147114.25957.71

Smith, S. K., Tayman, J., & Swanson, D. A. (2013). *A Practitioner's Guide to State and Local Population Projections* (Vol. 37). Dordrecht: Springer Netherlands. http://doi.org/10.1007/978-94-007-7551-0

Solecki, W. D., & Oliveri, C. (2004). Downscaling climate change scenarios in an urban land use change model. *Journal of Environmental Management*, *72*(1–2), 105–115. http://doi.org/10.1016/j.jenvman.2004.03.014

Stafoggia, M., Forastiere, F., Agostini, D., Biggeri, A., Bisanti, L., Cadum, E., … Perucci, C. A. (2006). Vulnerability to Heat-Related Mortality. *Epidemiology*, *17*(3), 315–323. http://doi.org/10.1097/01.ede.0000208477.36665.34

State Chamber of Oklahoma. (2014). Economic Assessment of Oil & Gas Tax Policy in Oklahoma. OKlahoma.

Stewart, I. D., & Oke, T. R. (2012). Local climate zones for urban temperature studies, 93. http://doi.org/10.1175/BAMS-D-11-00019.1

Su, M. D., Lin, M. C., Hsieh, H. I., Tsai, B. W., & Lin, C. H. (2010). Multi-layer multi-class dasymetric mapping to estimate population distribution. *Science of the Total Environment*, *408*(20), 4807–4816. http://doi.org/10.1016/j.scitotenv.2010.06.032

Sui, D. Z., & Zeng, H. (2001). Modeling the dynamics of landscape structure in Asia's emerging desakota regions: A case study in Shenzhen. *Landscape and Urban Planning*, *53*(1–4), 37–52. http://doi.org/10.1016/S0169-2046(00)00136-5

Sun, C., Wu, Z.-F., Lv, Z.-Q., Yao, N., & Wei, J.-B. (2013). Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *International Journal of Applied Earth Observations and Geoinformation*, *21*, 409–417. http://doi.org/10.1016/j.jag.2011.12.012

Swanson, D. A., & Tayman, J. (2012). *Subnational Population Estimates* (Vol. 31). Dordrecht: Springer Netherlands. http://doi.org/10.1007/978-90-481-8954-0

Tenerelli, P., Gallego, J. F., & Ehrlich, D. (2015). Population density modelling in support of disaster risk assessment. *International Journal of Disaster Risk Reduction*, *13*, 334–341. http://doi.org/10.1016/j.ijdrr.2015.07.015

Torrens, P. M., & O'Sullivan, D. (2001). Cellular automata and urban simulation: where do we go from here? *Environment and Planning B: Planning and Design*, *28*(2), 163–168. http://doi.org/10.1068/b2802ed

Turner 2nd, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., … Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proc Natl Acad Sci U S A*, *100*(14), 8074–8079. http://doi.org/10.1073/pnas.1231335100

Uejio, C. K., Wilhelmi, O. V, Golden, J. S., Mills, D. M., Gulino, S. P., & Samenow, J. P. (2011). Intra-urban societal vulnerability to extreme heat: The role of heat exposure and the built environment, socioeconomics, and neighborhood stability. *Health and Place*, *17*(2), 498–507.

http://doi.org/10.1016/j.healthplace.2010.12.005

UN-REDD. (2009). UN-REDD Programme. http://doi.org/10.1680/clh.2009.2.1

Valbuena, D., Verburg, P. H., Bregt, A. K., & Ligtenberg, A. (2010). An agent-based approach to model land-use change at a regional scale. *Landscape Ecology*, *25*(2), 185–199. http://doi.org/10.1007/s10980-009-9380-6

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., … Hibbard, K. (2011). The representative concentration pathways: an overview. *Climatic Change*, *109*, 5–31. http://doi.org/10.1007/s10584-011-0148-z

Verburg, P. H., Schot, P. P., Dijst, M. J., & Veldkamp, A. (2004). Land use change modelling: Current practice and research priorities. *GeoJournal*. http://doi.org/10.1007/s10708-004-4946-y

Voogd, H. (1983). *Multicriteria Evaluation for Urban and Regional planning. Pion*. Delft: Delftsche Uitgevers Maatschappij. http://doi.org/10.6100/IR102252

White, R. (1998). Cities and cellular automata. *Discrete Dynamics in Nature and Society*, *2*(2), 111–125. http://doi.org/10.1155/S1026022698000090

White, R., Engelen, G., & Uljee, I. (1997). The use of constrained cellular automata for high-resolution modelling of urban land-use dynamics. *Environment and Planning B: Planning and Design*, *24*(3), 323–343. http://doi.org/10.1068/b240323

White, R., Engelen, G., & Uljee, I. (2001). Modelling Land Use Change with Linked Cellular Automata and Socio-economic Models: A Tool for Exploring the Impact of Climate Change on the Island of St. Lucia. *Spatial Information for Land Use Management*, (Figure 1), 188–204.

Wilson, T. (2011). A review of sub-regional population projection methods. *The University of*, (December). Retrieved from http://gpem.uq.edu.au/qcpr-docs/SubRegionalProjectionMethodsReview.pdf

Wolf, T., & McGregor, G. (2013). The development of a heat wave vulnerability index for London, United Kingdom. *Weather and Climate Extremes*, *1*, 59–68. http://doi.org/10.1016/j.wace.2013.07.004

Wolf, T., McGregor, G., & Paldy, A. (2011). Integrated Assessment of Vulnerability to Heat Stress in Urban Areas. In *Coping with Global Environmental Change, Disasters and Security* (pp. 1091–1099). Springer Berlin Heidelberg. http://doi.org/10.1007/978-3-642-17776-7_67

Wu, F., & Webster, C. J. (1998). Simulation of land development through the integration of cellular automata and multicriteria evaluation. *Environment and Planning B-Planning & Design*, *25*(1), 103–126. http://doi.org/Doi 10.1068/B250103

Xu, Z., Sheffield, P. E., Su, H., Wang, X., Bi, Y., & Tong, S. (2014). The impact of heat waves on children's health: A systematic review. *International Journal of Biometeorology*, *58*(2), 239–247. http://doi.org/10.1007/s00484-013-0655-x

Yen, G. O., & Li, X. (2001). A constrained CA model for the simulation and planning of sustainable urban forms by using GIS. *Environment and Planning B: Planning and Design*, *28*(5), 733–753. http://doi.org/10.1068/b2740

Zhang, Z., Li, N., Wang, X., Liu, F., & Yang, L. (2016). A comparative study of urban expansion in Beijing, Tianjin and Tangshan from the 1970s to 2013. *Remote Sensing*, *8*(6). http://doi.org/10.3390/rs8060496

Zhu, Q., Liu, T., Lin, H., Xiao, J., Luo, Y., Zeng, W., … Ma, W. (2014). The spatial distribution of health vulnerability to heat waves in Guangdong Province, China. *Global Health Action*, *7*, 25051. http://doi.org/10.3402/gha.v7.25051

APPENDICES

APPENDIX A: Birth Rate (per 1000 people) of Oklahoma County (average 2000 – 2010 period)

Mother's Age	Birth Rate
10-14 years	0.6
15-17 years	18.5
18-19 years	52.6
20-24 years	67
25-29 years	63.2
30-34 years	45.3
35-39 years	19.7
40-44 years	3.7
45-54 years	0.2

Source: http://www.health.state.ok.us/ok2share/

APPENDIX B: Death Rate (per 1000 people) of Oklahoma County (average 2000 – 2010 period)

Age Group	male	female
<1 year	9.302833333	7.781
1-4 years	0.351181818	0.3596364
5-9 years	0.218	0.2358333
10-14 years	0.2769	0.1922857
15-17 years	0.635	0.305
18-19 years	1.37675	0.513
20-24 years	1.32575	0.428
25-29 years	1.373166667	0.67675
30-34 years	1.64275	0.8985
35-39 years	2.360416667	1.4710833
40-44 years	3.57725	2.2291667
45-49 years	5.435916667	3.3099167
50-54 years	7.993666667	4.8381667
55-59 years	10.89933333	6.9793333
60-64 years	15.81991667	10.683083
65-69 years	23.24208333	15.30775
70-74 years	35.51058333	23.677167
75-79 years	53.05516667	38.390167
80-84 years	83.96733333	59.329833
85+ years	158.718	137.41083

Source: http://www.health.state.ok.us/ok2share/

APPENDIX C: Multinomial Regression Result

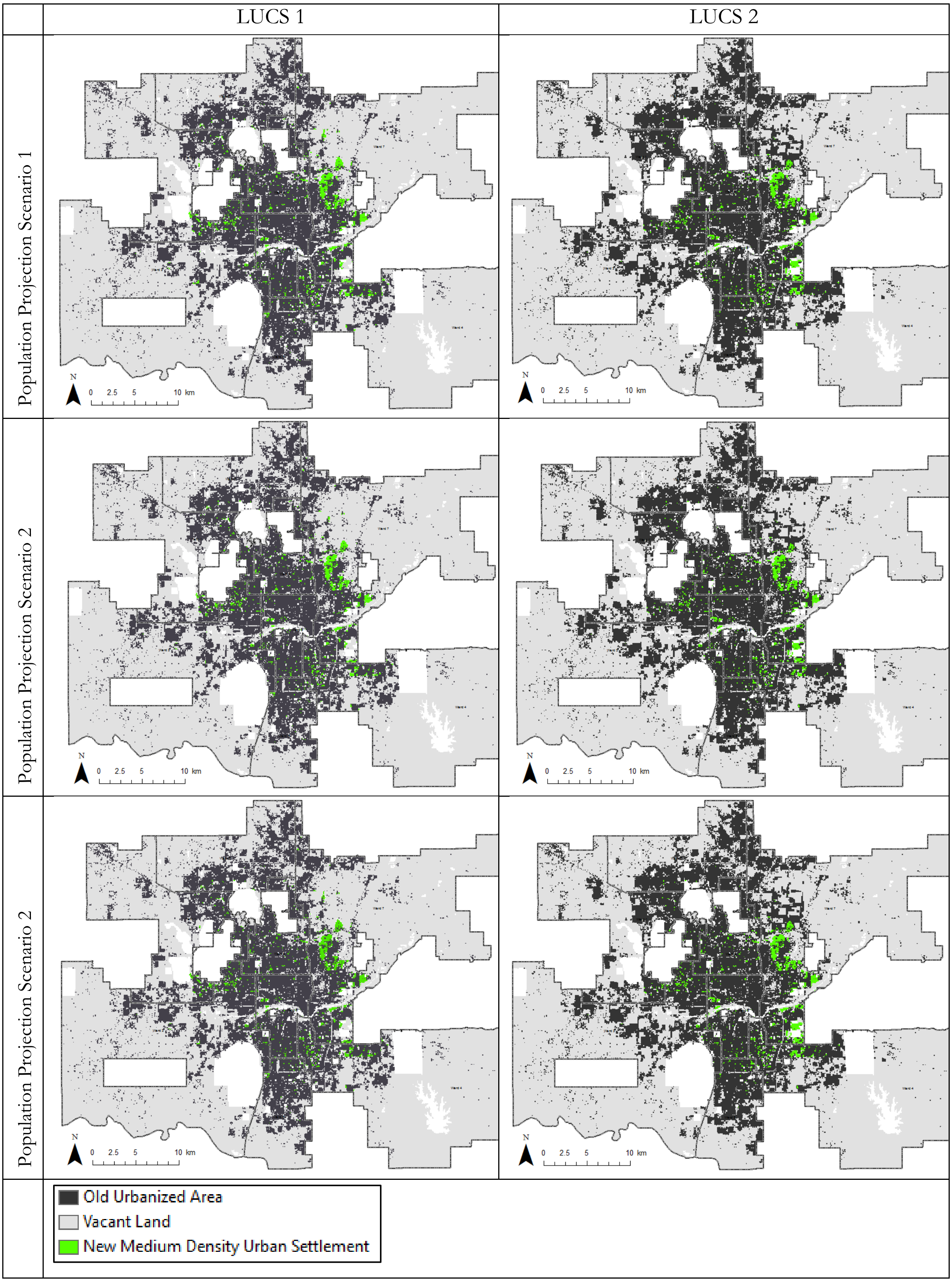
Parameter Estimates

urban00[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
1	Intercept	-29.019	17.739	2.676	1	.102			
	street_nor	4.691	5.528	.720	1	.396	109.010	.002	5536377.677
	sch_nor	21.881	16.702	1.716	1	.190	3183839661.354	1.935E-5	523983354173961500000000.000
	lake_nor	2.636	3.269	.650	1	.420	13.964	.023	8470.345
	dt_nor	-9.991	3.696	7.308	1	.007	4.582E-5	3.276E-8	.064
	nn1_00	17.694	2.704	42.820	1	.000	48341389.465	241385.914	9681136305.290
	nn2_00	8.471	1.700	24.824	1	.000	4776.030	170.529	133762.937
2	Intercept	-10.992	2.251	23.846	1	.000			
	street_nor	4.832	1.914	6.372	1	.012	125.502	2.945	5347.477
	sch_nor	1.865	1.907	.957	1	.328	6.455	.154	270.970
	lake_nor	.335	1.038	.104	1	.747	1.398	.183	10.690
	dt_nor	-.186	1.064	.031	1	.861	.830	.103	6.688
	nn1_00	5.800	1.559	13.842	1	.000	330.255	15.557	7010.959
	nn2_00	10.024	.703	203.194	1	.000	22556.789	5684.808	89503.246

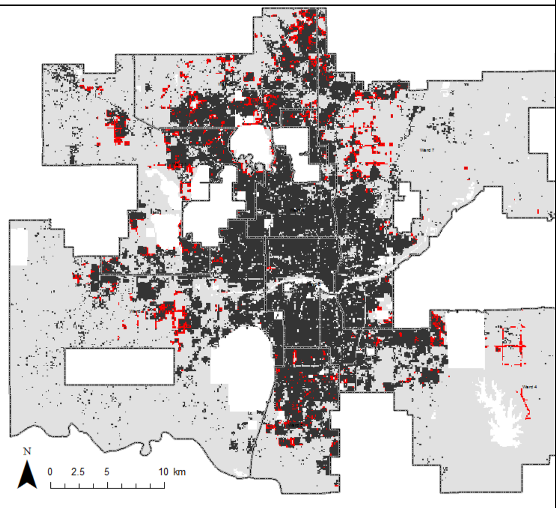
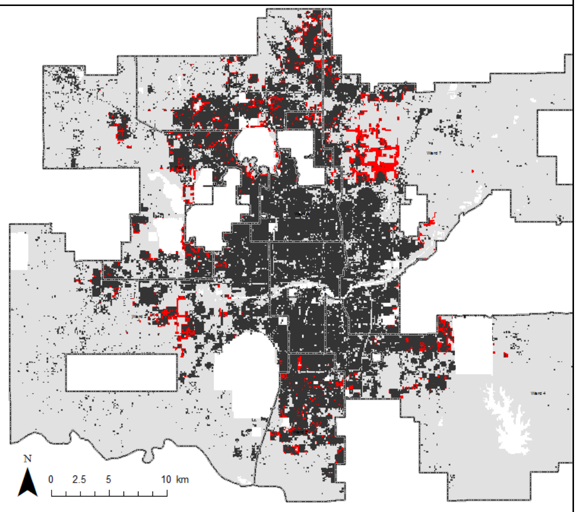
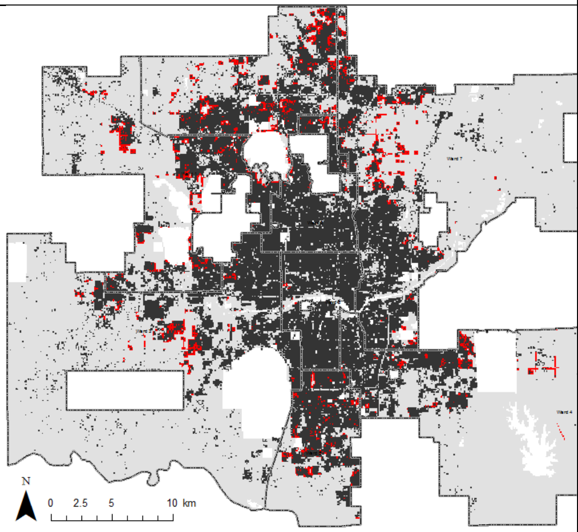
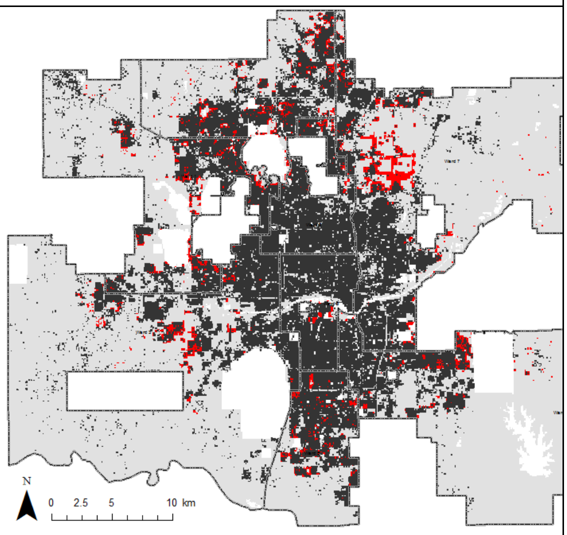
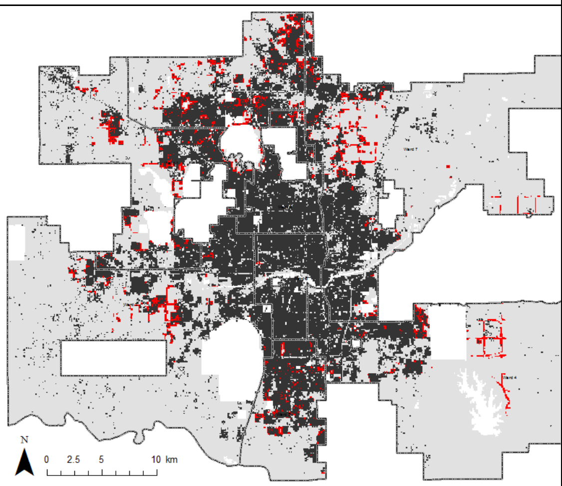
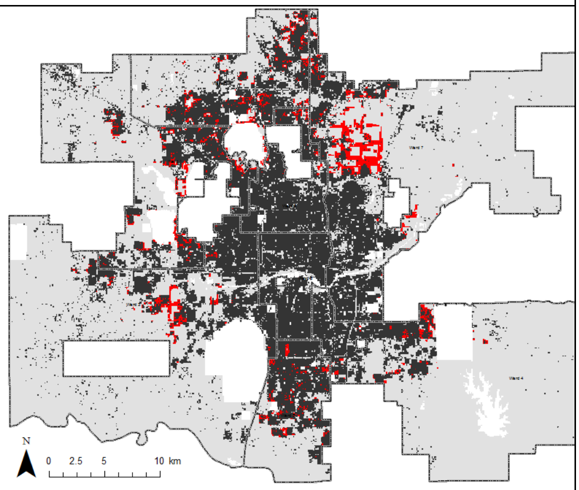
a. The reference category is: 0.

Source: SPSS

APPENDIX D: Projection of High Density Urban Settlement in 2030



APPENDIX E: Projection of Low Density Urban Settlement in 2030

	LUCS 1	LUCS 2
Population Projection Scenario 1		
Population Projection Scenario 1		
Population Projection Scenario 1		
	Old Urbanized Area Vacant Land New Low Density Urban Settlement	