"Towards Urban Sustainability: A Framework for Understanding the Applicability of SDGs to small and medium size cites (SMSC)"

by

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ABSTRACT

United Nations (UN) News states that understanding upcoming urbanization trends is crucial to implementing the 2030 Agenda for Sustainable Development. This agenda consists of 17 sustainable development goals (SDGs) that the UN hopes all countries will achieve by 2030. Research has shown the importance of involving stakeholders and practitioners in solving sustainability challenges. However, doubts remain about the feasibility of implementing SDGs at all spatial levels, especially in small and medium-sized cities (SMSC) involving citizens in decision-making. This research aims to fulfill four objectives sing various techniques: (1) creating survey instruments to gather residents' awareness/familiarity, concern/urgency, perception, involvement, behavior, and intended behavior about sustainability; (2) evaluating the same characteristics within different groups and their relationship with each other; (3) analyzing land use and land cover (LUCC) changes in 10 cities in Alabama, a southeast US (SEUS) state, to understand the impact of the changing urban landscape; and (4) creating a data reporting platform for a growing small city in Alabama, Auburn to serve as a centralized location for viewing and collecting information about the area's goals.

The first study creates a validated survey instrument that can be used by cities to evaluate the awareness/familiarity, concern/urgency, perception, involvement, behavior, and intended behavior of their residents towards sustainable practices based on the UN SDGs. The second study conducts a multigroup comparison of different demographic subgroups' attitudes towards sustainability practices and creates a model to evaluate the relationship between the aforementioned variables. The results reveal different responses among demographic groups and concern/urgency being the most influential factor

leading to behavior changes, although other factors are also significant.

The third study analyzes LUCC changes in 10 cities in Alabama and predicts future growth with a business-as-usual scenario using a cellular automata model. The fourth study documents the creation of a data reporting and visualization platform for reporting SDG information for Auburn, Alabama. This platform uses the Open SDG Data Reporting Platform provided by UN, Python, Ruby, GitHub Pages, Jekyll, and ArcGIS Online to provide a current picture of how applicable the SDGs are at a city level and how a city like Auburn performs on the scale of SDGs.

Overall, this study provides a framework for SMSC in the SEUS to promote citizen engagement, understand the physical changes due to the exponential increase in population, and provide a centralized platform for reporting progress towards sustainable development.

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LIST OF ABBREVIATIONS

SMSC	Small and Medium Size Cities
SEM	Structural Equation Model
EFA	Exploratory Factor Analysis
CFA	Confirmatory Factor Analysis
CTT	Classical Test Theory
MGCFA	Multigroup Confirmatory Factor Analysis
LUCC	Land Use Land Cover
SDG	Sustainable Development Goals
SEUS	Southeast US
MTurk	Mechanical Turk

CHAPTER 1: INTRODUCTION

Urbanization, characterized by increase in population density and associated infrastructure development, is increasing worldwide (United Nations 2018). According to the United Nations (UN), the year 2007 was the year when more people in the world began to live in cities than in rural regions (North Carolina State University 2007), with 55 % of the world's population living in cities in 2018 (United Nations 2018). The urbanization of the United States (US) has undergone significant transformation over the past two centuries, evolving from a primarily rural and agricultural nation to an industrialized one. The process of urbanization was gradual, with the country not reaching a majority urban population until the period between 1910 and 1920, as reported by the 2010 US Census (US Census 2010). Today, over 80% of US citizens reside in urban areas, a trend that continues through decades (US Census 2010).

Urbanization can be beneficial for various reasons but can have other consequences as well. Benefits range from better living standards, economic growth, access to education, medical facilities, and better infrastructure. However, it can also result in excess and unmanaged use of resources that can lead to environmental problems, lack of proper living standard, crime, and inequality. With a growing urban population and increased human activities, the world needed guidance and directions which would be a blueprint for a sustainable life, combining social, economic, and environmental aspects of living. Meeting this demand, the 2030 Agenda for Sustainable Development, called Sustainable Development Goals (SDGs), was created to provide all countries with sustainable solutions to pertinent problems, sharing their experiences, learning from one another, holding each other accountable for implementation of equitable and justifiable solutions.

Urbanization in the US

According to 2018 Revision of World Urbanization Prospects produced by the Population Division of the United Nations Department of Economic and Social Affairs (UN DESA), North America is the most urbanized region of the world with 82% of its population living in urban areas in 2018 (United Nations, Department of Economic and Social Affairs, Population Division 2019) up from 64 % in 1950 (Center for Sustainable Systems, University of Michigan 2020). Between 2000 and 2010 there was a 15% increase in urban areas in the US (Center for Sustainable Systems, University of Michigan 2020). In 2019, there were over 300 urban centers in the United States with populations exceeding 100,000, with New York City, the country's largest, having 8.4 million residents (Center for Sustainable Systems, University of Michigan 2020). The average population density in the United States' major cities is 1,593.5 people per square mile, while it is only 34.6 people per square mile outside of metropolitan areas (US Census Bureau 2015). USA is divided into 5 regions according to their geographic position on the continent: Northeast, Southwest, West, Southeast, and Midwest. The Southeast region comprise of the states of South Carolina, Virginia, West Virginia, North Carolina, Mississippi, Arkansas, Tennessee, Florida, Georgia, Alabama, Kentucky and Louisiana. In the latter half of the 20th century Southeast US (SEUS) experienced rapid growth, both in cities and suburbs, with a population growth rate of 40% in the last six decades (North Carolina State University and the U.S. Geological Survey). As the population increases so does urban sprawl which signifies urban footprint expansion (Nechyba and Randall 2004). Urban sprawl has resulted in loss of rural land, green space reduction and increased traffic, air pollution, school crowding, and taxes (Everything Connects 2013). According to the study conducted by Norman J., et al. (2006) low-density development has 2.5 times the greenhouse gas (GHG) emissions and twice the energy usage of high-density development on an annual per capita basis. They also have 1.5 times the annual GHG emissions and the same energy consumption as high-density development on an annual per capita basis (Norman J. et al. 2006). Numerous studies demonstrate that urbanization degrades environment causing problems such as land insecurity, worsening water quality, excessive air pollution, noise, problems of waste disposal and many more (Basak 2018; C and H.O 2018; Fiorini et al. 2019; Abd Rahim et al. 2018). However, urban areas can also be thriving sustainable communities. A sustainable urban area is characterized by the preservation of quality environment, use of renewable and efficient energy resources, the maintenance of a healthy population with access to health services, and the presence of economic vitality, social equity, and engaged citizenry (Center for Sustainable Systems, University of Michigan 2020).

Urban areas, cities' sustainable policies in US, and UN SDGs

Urban areas are synonymous with cities in this study. Cities are interpreted as local and subnational authorities with responsibilities for an urban area and acts as a driving force for challenges relating to unplanned urbanization, climate change, inequal distribution of economy and opportunity, shifting economies, changing demographic trends and other developmental challenges. This has led to creation of major networks and organizations for cities dedicated to solving above-mentioned challenges such as International Council for Local Environmental Initiative, 100 Resilient cities, Council of Cities Mayor, Cities Climate Leadership Group and many more. Their central focus is city sustainability i.e., to establish a resilient environment that caters to the needs of all city dwellers, present and future. This is achieved by adopting a holistic approach that encompasses an understanding of the various systems that make up the city, as well as the interdependencies and hazards they may face, collectively known as urban integrated services (UIS) (Grimmond et al. 2018) . Prior to implementing any policies or plans for urban development, it is imperative to obtain detailed information on a city-block scale in order to create a resilient urban area. This requirement extends not only to stakeholders and policymakers but also to citizens, institutions, and responsible authorities, who must provide support and information on an ongoing basis within the urban area. Mitigation, particularly in risk management, necessitates a planned and strategized public communication component so that the same message is conveyed across different sectors. This approach has been instrumental in comprehending urban sprawls, the need for climate action plans, the conservation of natural habitats, the establishment of early warning systems for hazards, particularly those related to climate change, and effective communication among policymakers, officials, and the public.

Atlanta, GA, known as the capital of the South, is taking various initiatives to address the environmental and climate issues that accompany urbanization. Their efforts include developing a climate action plan to reduce greenhouse gas emissions, launching the Atlanta City Design project for sustainable and equitable growth, improving transportation systems to connect different parts of the city, and investing in renewable energy. Similarly, Miami, FL, is actively managing flood risk and raising public awareness with the Miami Beach Rising Above Resilience communication approach and the Miami Beach - eGov mobile app for residents to report flood incidents. Birmingham, AL, faces a severe economic impact from climate change and has devised a climate action plan, but it suffers from political differences in ideas and funding. However, cities in North Carolina, South Carolina, and West Virginia lack effective climate action due to inadequate research, collaboration, modeling, open data policies, and city-wide networks of sensors. Therefore, integrating urban services is crucial for all cities, regardless of their size, to address the challenges of climate change. Cities situated in the United States, particularly those in or near the southeastern region, would benefit from a comprehensive framework that includes stakeholder engagement and citizen involvement from the outset. By implementing an open data policy, citizens can better understand and utilize these services, thereby promoting the development of more sustainable and resilient cities. This approach can also foster a culture of learning and adaptation, which is crucial for achieving long-term urban sustainability. To achieve this, cities must adopt an integrated approach to environmental management, including measures to counter urban sprawl. Furthermore, linkages between community, ecology, and economy must be established, with coordinated stakeholder interaction, and progress must be measured and reported regularly. Only by taking these steps can cities become truly sustainable and resilient in the face of challenges posed by climate change.

The UN has been a leader in advocating sustainability and tackling global environmental and social challenges. The UN's commitment to sustainable development efforts began around 1970s when it established programs and institutions to promote sustainable development and improve the quality of life for individuals across the world (UN, 1970). The origins of the SDGs can be traced back to the United Nations Conference on Environment and Development (UNCED) in 1992, also known as the Rio Earth Summit. During this event, world leaders adopted Agenda 21, which served as a comprehensive action plan for sustainable development (United Nations, 1992). Subsequently, in 2000, the UN adopted the Millennium Development Goals (MDGs), which were a set of eight objectives aimed at addressing critical development challenges, such as poverty, hunger, and education (United Nations, 2000). Although the MDGs made significant strides in many areas, they also revealed the need for a more comprehensive approach to sustainable development that recognizes the interrelatedness of social, economic, and environmental issues. This recognition spurred the development of the SDGs, which were adopted in 2015 as part of the 2030 Agenda for Sustainable Development. The 17 SDGs and 169 targets, which addresses the interlinked social, economic, and environmental challenges facing the world today, aim to eradicate poverty, promote equality, economic development, conservation, and climate action, and ensure prosperity for all (United Nations, 2015). These objectives are comprehensive, universal, and ambitious, reflecting the understanding that sustainable development cannot be achieved in isolation and requires coordinated efforts from all countries and stakeholders (United Nations, 2015). They also provide a platform for countries to share their experiences, learn from one another, and hold each other accountable for providing sustainable solutions to pressing global problems. The 17 SDGs (Figure 1.1) include the following:

Goal 1: no poverty.

Goal 2: zero hunger.

Goal 3: good health and well-being.

Goal 4: quality education.

Goal 5: gender equality.

Goal 6: clean water and sanitation.

Goal 7: affordable and clean energy.

Goal 8: decent work and economic growth.

Goal 9: industry, innovation, and infrastructure.

Goal 10: reduced inequalities.

Goal 11: sustainable cities and communities.

Goal 12: responsible consumption and production.

Goal 13: climate action.

Goal 14: life below water.

Goal 15: life on land.

Goal 16: peace, justice, and strong institutions, and

Goal 17: partnerships for the goals

Figure 1.1: UN SDGs. Adapted from UN, 2015

While the SDGs aim to benefit the entire world, their importance is particularly pronounced in urban centers. These areas are characterized by a high concentration of people, making sustainable policies a critical concern. Urban centers should assess themselves against the SDGs to identify gaps in preparedness and resiliency. This assessment is crucial as it can drive efforts to enhance sustainability and improve the well-being of citizens and cities as a whole.

Importance of study - small and medium size cities

As mentioned above, cities characterized by high population density and increased infrastructural development are crucial areas of social changes, economic opportunities, and associated environmental impacts. While these changes can create new opportunities for development, they can also pose significant challenges that must be addressed to ensure the livability and sustainability of cities. UN recognizes cities to play a crucial role in achieving the SDGs. According to a special study published by the Intergovernmental Panel on Climate Change (IPCC) in 2014, population migration and growth will be concentrated in small and medium-sized cities (SMSC) in developing countries in the next few decades (Seto K.C et. al. 2014). This trend is supported by analyses of the 515 fastest growing cities in the United States during the past decade, which revealed that the population of SMSC expanded at a faster rate than that of major cities, while some large cities experienced an exodus of residents from the city center to surrounding suburbs, even in the US (Locker 2017). Because of climate change, more people are expected to live in SMSC (Seto K.C et. al. 2014), it's vital to consider these city types. Given the anticipated increase in population in SMSC, it is critical to consider the unique challenges faced by these city types to ensure their resilience and sustainability. SMSC are distinct from large cities in several ways, including demographic characteristics, economic activities, and infrastructure development. For example, SMSC often have lower population densities, fewer economic opportunities, and less advanced transportation and communication networks than their larger counterparts. According to a study by the World Bank, SMSC in developing countries have lower per capita GDP than major cities, but they offer better opportunities for poverty reduction and social inclusion. This is because SMSC are often less congested, have more affordable housing options, and offer a better quality of life for their residents (World Bank, 2013). However, SMSC may also face unique challenges, such as limited access to resources and expertise, difficulty attracting businesses and talent, and vulnerability to climate change impacts. Consequently, it is important to understand the strengths and weaknesses of SMSC to facilitate the development of policies and strategies that take into account the specific needs and opportunities of SMSC to ensure their sustainability and livability. In this regard, SMSC, in particular, can learn from one another to achieve these objectives. As a result, the creation of a template to aid in the provision of substantive assessments for cities that do not belong within the metropolitan framework, i.e., focusing on SMSC rather than attempting to develop a template for large cities such as New York City or Los Angeles, is necessary.

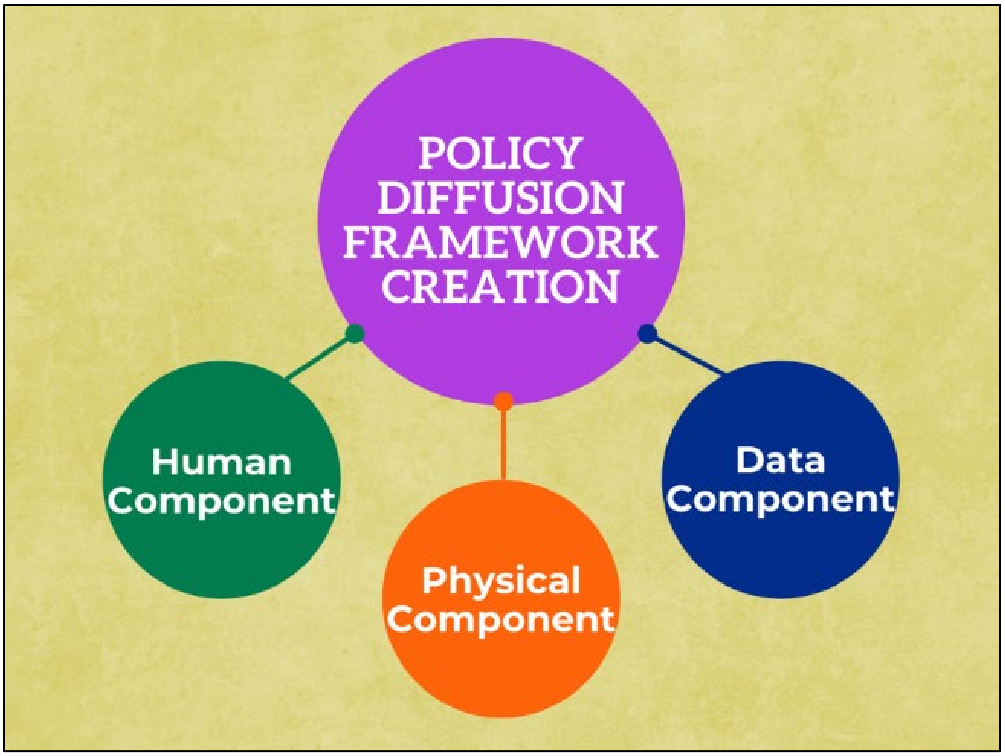
Possible solutions towards sustainability in SMSC

The UN SDGs, mentioned above, are mostly collected at the national level, but their applicability at the local level is critical to comprehend. A survey instrument is a good indicator for assessing such comprehension and engagement in a variety of fields (Wastberg et.al. 2020; Beecher et al. 2021). While there are multiple survey studies conducted in higher education on sustainability, and environmental studies, which focus on awareness, assessment of knowledge, attitude, and practice, not enough studies have been conducted that incorporates residents' views to inform sustainable plans and policies. Most of the survey instruments created focus on collecting policy perspectives about sustainability and sustainable development goals (Gadema and Oglethorpe 2011; Aljerf 2016; Guan et al. 2020; Yamane and Kaneko 2021). Additionally, there is only few studies that specifically use survey instrument to collect citizens' awareness, perception, knowledge, attitude, behavior, concern, intended behavior, and practice related to sustainability and sustainable goals to inform future plans and policies.

SDGs, as aforementioned, aim to overcome global challenges which include poverty, inequality, and even the effects of climate change. Sustainable development, though significant everywhere, is extremely important for urban areas. As mentioned above, urbanization is seen prevailing all around the world with more people living in urban areas than in rural areas from 2007 (Ritchie and Roser 2018) and the trend continues to increase. The UN has identified this as a critical issue, highlighting the importance of considering the evolving urban landscape in the pursuit of a sustainable future. According to the United Nations Department of Economic and Social Affairs (2016), understanding the key trends in urbanization that are expected to unfold in the years ahead is essential to the successful implementation of the 2030 Agenda for Sustainable Development, which includes a new framework for urban development. Remote sensing technologies such as LIDAR and unmanned aerial vehicles (UAVs) can prove to be useful in monitoring progress in spatially small urban areas such as SMSC. Otherwise, for larger areas/cities, Landsat Mission—launched since 1972— which is free and has higher spatial (30m) and temporal (11-13 days) resolution can be used extensively for monitoring progress (Loveland and Dwyer 2012). There are other high spatial resolution satellites such as Sentinel, SPOT, RapidEye, ALOS, Worldview, GeoEye, KompSat, SkySat, TripleSat, and Pléiades (Yang 2018). Google Earth Engine (GEE) can also provide high spatial and spectral resolution data within its platform to monitor phenomenon that can help reduce pollution and understand weather conditions to plan for immediate actions in case of weather-related hazards, among others (Mutanga and Kumar 2019). These can help formulate better plans and policies by understanding the multi-faceted influences of nature as well as human activities for improving the environment and standard of living for all. Additionally, locally collected geospatial dataset through ground-based methodologies and other technologies such as global positioning systems (GPS) combined with remote sensing techniques and GIS analysis can provide well-informed scenarios for better future policies which can influence various aspects of community development to make it more resilient and sustainable.

Similarly, data contains knowledge that can be used to explain patterns and generate visualizations to convey various information to the public. Many studies have been undertaken to examine the potential of using data to assist cities in better planning, resilience, and sustainability. A study by Wastberg et.al. (2020) aims to gather feedback from urban planners on tools and interfaces for visual representation of environmental data, as well as existing development needs. This will help encourage informed design decisions in the development of urban planning tools. The paper emphasizes the importance of investigating the potentials and challenges of data visualization in urban planning, as environmental data must be well represented for increased communicative value. Results show that environmental visualization apps must be enhanced regarding user friendliness and information management in order to improve effectiveness (Wastberg et.al. 2020). Furthermore, the study by Huang, Song, and Hu (2021) explores the idea of using spatial data for resiliency. This study synthesizes a cross-disciplinary literature review on implementing spatial data for coastal community resilience drawing on 142 studies. The authors studied papers based on three research questions to answer them. They investigated the data types suitable for gathering situational awareness on coastal resilience. They examined the spatial data that could be linked to applications related to coastal resilience, as well as the gaps in spatial data concerning coastal resilience applications. To understand these research issues, the authors evaluate papers based on three criteria: spatial data availability, functionality availability, and limitations. As a result of the growing availability of data and comprehensive growth in data processing, the use of spatial data for coastal community resilience assessment has broadened. Therefore, it is critical to create a data inventory to examine the existing condition and various demands to become a smart and sustainable city. In addition, effectively communicating progress towards sustainable growth is a challenging task, which involves a clear and understandable presentation of data. This can be addressed using indicators. However, according to Janoušková, Hák, and Moldan (2018), one of the key challenges of using indicators to measure sustainability is the accurate interpretation of the resulting data. Indicators serve an instrumental function in measuring progress and can play an important role in promoting social learning. By helping to organize policy issues, construct indicator structures, and explain the various meanings of the information conveyed by indicators, they can facilitate better decision-making and policy development. Therefore, it is critical for cities to develop comprehensive data inventories that incorporate the use of well-documented indicators to evaluate and visualize the current state of sustainability, and to plan for future actions accordingly (Janoušková, Hák, and Moldan 2018).

Therefore, this project aims to provide a specialized framework for cities, especially SMSC, in the United States to address such sustainability issues. This framework allows cities to assess their current environmental trajectory, their citizens' expectations, and values, and provide visualization tool (shown in Figure 1.2) to compare to similar cities, rather than making a comparison with larger cities. This initiative will have a more extensive impact on a greater number of municipalities, leading to possibilities for implementing and evaluating sustainable projects and policies that improve the lives of residents. This study also contributes to the growing body of research on SMSC by assessing if local governments are meeting the UN SDGs



and communicating sustainability and climate change through a framework designed to share knowledge about the city. This model, hopefully, will be replicated in different SMSC to achieve the same knowledge transfer goal among citizens, stakeholders, and local government.

Objectives

In order to create such a framework this study has four objectives that targets three different spatial scales as shown in Figure 1.3 and are as follows:

1. To create and validate a survey instrument that gathers information on awareness, concern, perception, involvement, intended behavior, behavior about or with UN SDGs among SEUS

Figure 1.2: Overall framework for the dissertation

residents.

2. To gather, compare, contrast, and comprehend information on awareness, concern, perception, involvement, intended behavior, behavior about or with UN SDGs among SEUS residents.

3. To examine and showcase the need to assess urban growth of Alabama cities, past to future, manifesting the implementation of SDGs in SMSC.

4. To create a data inventory and visualization platform for a SMSC, Auburn City in Alabama, involving primary and secondary data to examine the level of sustainability and resiliency comparing to UN's SDGs.

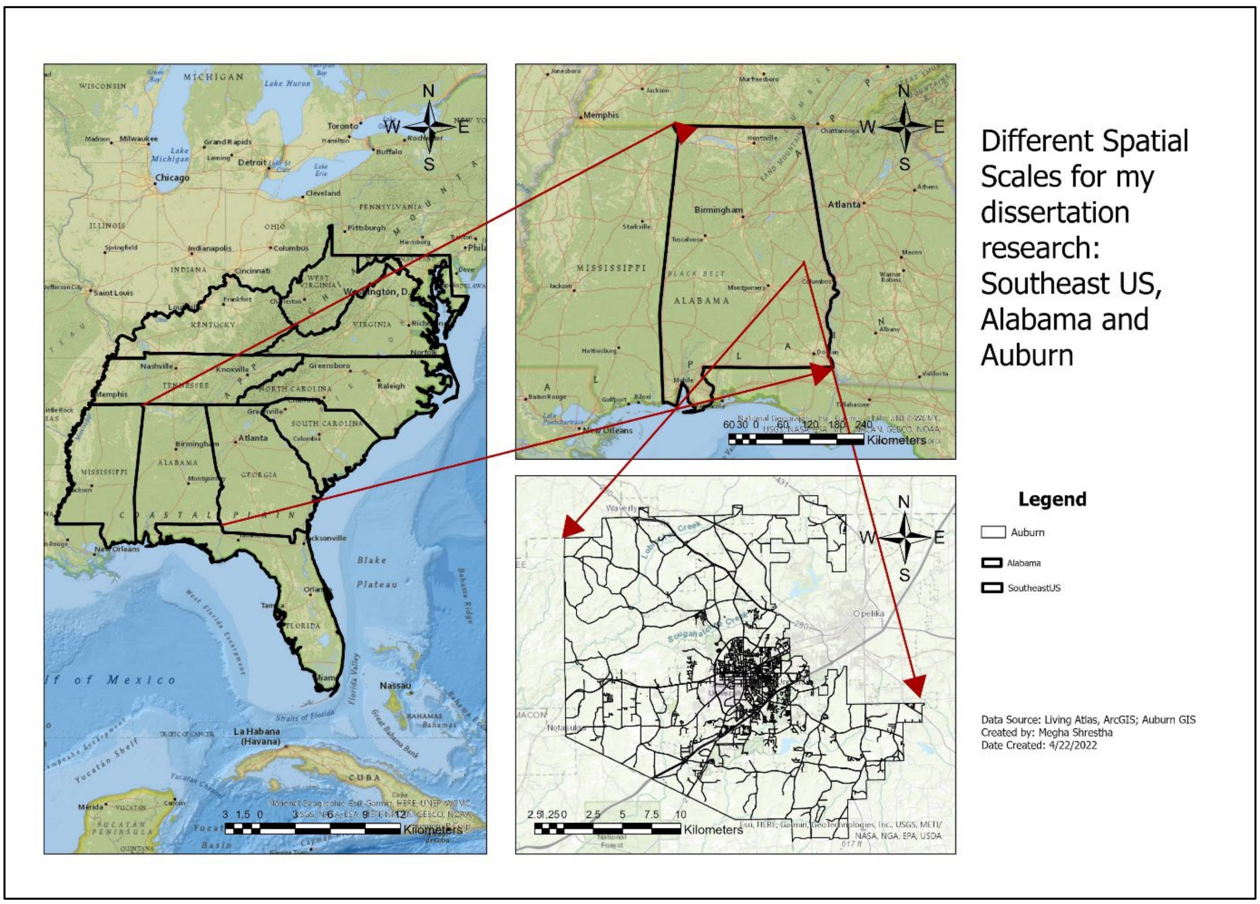


Figure 1.3: Locational Map for the objectives of the study

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CHAPTER 2: DEVELOPMENT AND VALIDATION OF A SURVEY INSTRUMENT FOR SDGs UNDERSTANDING IN SEUS RESIDENTS

Introduction

Sustainability as a concept was first introduced in forestry where its meaning was associated with harvesting (Wiersum 1995). The Brundtland Report in 1987 popularized sustainability as a policy idea, which has since been prominent in policy-oriented research to determine what public policies should accomplish (Kuhlman and Farrington 2010). Today, sustainability encompasses three pillars —social equity, economic viability, and environmental protection—to promote development while ensuring that resources are preserved for future generations (Kuhlman and Farrington, 2010). There is a widespread debate over the scope of sustainability. Many people believe that pursuing sustainability entails only prioritizing natural resources, even though sustainability is inextricably linked to the technological and human progress, with nature conservation playing a significant role in both (Kuhlman and Farrington, 2010). Therefore, achieving sustainability is inextricably linked with human population and resources used. In Chapter 1, the trends of population growth and urbanization worldwide are discussed, which have led to the formation of cities. The chapter also highlights the impacts that cities can have on achieving sustainability goals. Moreover, it emphasizes the necessity of a bottom-up approach for engaging citizens for sustainable development. Despite the importance of citizen engagement, there remains a lack of research on understanding the characteristics of residents that can lead to sustainable behavior. Additionally, the chapter also explains the concept and need of UN SDGs as a set of universal goals created to achieve sustainable development for all. These goals are more global than local in character, but they serve as a foundation for gathering data and comparing residents' perceptions of urban sustainability and sustainable development in this chapter. This statement from the UN news (2018), "Understanding the key trends in urbanization likely to unfold over the coming years is crucial to the implementation of the 2030 Agenda for Sustainable Development, including efforts to forge a new framework of urban development," demonstrating the value of understanding urban sustainability to achieve the goals and improve human lives in general. There are multiple initiatives taken all over the world towards creating a sustainable and better future. Hamburg (Germany), Magdeburg (Germany), St. Petersburg (US), and Milwaukee (US) were among the first cities chosen to assess the challenges and opportunities associated with their existing sustainability standards, as well as the possibility of incorporating SDGs into the broader sustainability planning process (Krellenberg et al. 2019). Also, the Comprehensive Assessment System for Built Environment Efficiency (CASBEE) has been effectively implementing and assessing sustainable measures at the local level by evaluating quality and environmental load perspectives (Kawakubo et al. 2018). Koch and Krellenberg (2018) focus on analyzing the contextualization of global urban goals at a national level. Their findings reveal that only a small number of the original SDG 11: Sustainable Cities and Communities targets and indicators set by the United Nations, are implemented in the German cities. Therefore, considerable revisions were made in line with Germany's key sustainability challenges. The results reveal that SDG 11 contextualization and sustainable urban development are still happening in Germany and further amendments and obligations must be made (Koch and Krellenberg 2018). This shows the importance of understanding sustainability in a local context.

According to the United Nations Department of Economic and Social Affairs (UN DESA) 2018 Revision of World Urbanization Prospects, North America is the world's most urbanized region, with 82 % of its population living in cities in 2018 (UN DESA, Population

Division 2019). The US has also taken several steps in the direction of long-term solutions at various levels - national, state, county, and city. Living Cities Report in 2009 found that over 75% of the 40 largest U.S. cities surveyed have plans for reducing greenhouse gasses in the coming years (Living Cities, 2009). The Environment Protection Agency (EPA) also offers many clean energy programs, information, training opportunities, grants, resources, and tools to assist local governments. In 2009, the U.S. Department of Housing and Urban Development, Department of Transportation, and Environmental Protection Agency created the Partnership for Sustainable Communities to promote sustainable communities through better access to affordable housing, more transportation options, and lower transportation costs. The San Jose-Sunnyvale-Santa Clara metro region in California placed first on the SDG Index of the city ranks based on 49 indicators across 16 of the 17 SDGs (Sustainable Development Solutions Network 2017). As per the report from the Center for Sustainable Systems of the University of Michigan, by August 2019, 1,060 mayors have signed on to the 2005 U.S. Mayors Climate Protection Agreement, committing to reduce carbon emissions below 1990 levels, in line with the Kyoto Protocol in USA (Center for Sustainable Systems, University of Michigan. 2020). There are national and international associations promoting collaboration and cooperation between local, regional, and national governments.

One such international organization which is very active in this field is the International Council for Local Environmental Initiatives (ICLEI), whose focus is developing locally designed initiatives to achieve sustainability goals. In the USA, ‘Smart Growth America’ serves as a coalition working to improve the planning and building of towns, cities, and metro areas. The ‘Solar Outreach Partnership’ is a component of the U.S. Department of Energy’s SunShot Initiative to make solar energy cost-competitive with other energy technologies. The Solar

Outreach Partnership provides local governments with guidance on community-wide deployment of solar power. Local governments all over the USA have launched several projects aimed at achieving the common goal of sustainable development, and they need citizens to both understand and support sustainability for initiatives to be effective. However, there have not been enough studies to understand citizen's participation in such project and policy development. Hence, this paper outlines the development and validation of a survey instrument aimed at gathering data regarding several aspects of a population's awareness/familiarity, concern/urgency, perception, involvement, behavior, and intended behavior about sustainability practices-based on UN SDGs, and how they are related to each other and other demographics elements as an initial piece of a larger research project which is explored in Chapter 3. The purpose of the larger project is to provide a framework that city governments in SMSC may use to determine which policies their residents support and why. The urgent concern, however, is to develop a methodology on how to adapt the variety of existing sustainability and SDGs survey instruments, modify them, and/or design and evaluate new instrument scales to satisfy these requirements. This study also aims to use statistical techniques such as factor analysis to understand the latent structure of sustainability responses. Factor analysis is a statistical technique used to identify underlying dimensions, or factors, that explain the variance in a set of observed variables (Bryant and Yarnold 1995) and latent structure models are models used in survey analysis to identify unobserved or latent variables and the relationships between them (Asparouhov and Muthén 2009). Therefore, the purpose of our research is (1) collect SEUS residents' awareness/familiarity, concern/urgency, perception, involvement, behavior, and intended behavior (latent variables) about sustainability and the SDGs (2) understand which latent variables load with the items provided; and (3) provide a reliable and validated survey to collect such information that can guide present and future development plans and policies.

Survey Instruments as a measure of understanding SDGs

MacDonald et al. (2018) explores the importance of involving stakeholders in the solutions of different sustainability challenges. The findings revealed that sustainable community plans are still being developed and implemented in a variety of communities around the world, with local organizations serving as implementation partners, acting as an incentive for local government investments in community sustainability, and leading to a sustainable future (MacDonald et al., 2018). Therefore, to enhance such partnership it is crucial to understand and involve residents of a city in decision making. A survey instrument is a useful metric to assess such understanding and involvement across numerous fields. Clark and Libarkin (2011) designed, implemented, and scored a valid and reliable mixed-methods survey instrument to gather conceptions of plate tectonics and use the results to better communicate various information related to it. Similarly, researchers used a survey to differentiate the possible awareness levels between Alabama and Hawaii college students about sustainability, though there was not a significant difference between awareness between the college students, Hawaiian students took more action and were more likely to take further actions to make their college sustainable (Emanuel and Adams 2011). Walker and McNeal (2012) developed and validated a survey instrument for assessing climate change knowledge and views using factor analysis and classical test theory. Undergraduate business students' attitudes, beliefs, and perceptions about sustainability were evaluated pre and post curriculum change using a semi-structured questionnaire applied across two campuses of James Cook University, Australia (Eagle et al. 2015). Awareness and knowledge of the SDGs were examined using a cross-sectional survey in

Osun State University, Southwestern Nigeria, chosen via multi-stage sampling. Researchers discovered a low level of awareness of and attitudes toward the SDGs, which has serious negative implications for SDG attainment (Omisore et al. 2017). Libarkin et al. (2018) also designed and examined a climate change concept inventory with high validity and reliability. Abiola, Joseph, and Rachael (2018) designed a survey instrument to assess the general perception of librarians in Osun State in the attainability of the sustainable development goals. They found optimistic responses about achieving gender equality by empowering all women and girls. Additionally, they observed a widespread belief that SDGs can protect, restore, and promote the sustainable use of terrestrial ecosystems, manage forests sustainably, and combat desertification, and that library and information services are relevant to the attainment of the sustainable development goals in Nigeria. Melles (2019) used a survey to investigate the knowledge and attitudes of postgraduate United Kingdom (UK) students enrolled in one-year taught sustainability degrees on the multidimensional issues of sustainable development. The study discovered that this cohort was able to recognize and respond to many problems of strong and weak sustainable development issues, rather than demonstrating previously documented knowledge gaps. The survey's findings and qualitative remarks, however, show that students are opposed to major interventions in social, political, and economic life. Another survey was used to determine the awareness level of University of Malaya students towards SDGs based on knowledge, attitude, and practice in Indonesia. They found a strong correlation between attitude and practice towards SDGs in university students (Afroz and Ilham 2020). Kazakova et al. (2020) undertook a sociological study of university students, primarily from southwestern Siberia, to assess their grasp of the Sustainable Development Goals and global concerns confronting humanity. They surveyed respondents to determine which world problems should be addressed first: ecological, social, or economic. Respondents chose differently for ecological, social, or economic problems as the most pressing at global, national, and regional scale as their priority - more concerned about ecological problems at global level and economic and social problems at national and regional levels. Smaniotto et al. (2020) employed a Likert scale-based online questionnaire with 70 items to examine first-year students' awareness, knowledge, and attitudes about SDGs and sustainability at nine Italian universities. Most of the survey instruments created focuses on collecting already established policy perspectives about sustainability and sustainable development goals (Gadema and Oglethorpe 2011; Aljerf 2016; Guan et al. 2020; Yamane and Kaneko 2021) in higher education and environmental studies but there is little work that specifically use survey instrument to collect residents' awareness/familiarity, concern/urgency, perception, involvement, behavior, and intended behavior related to sustainability and sustainable goals to inform future plans and policies.

In the development of the survey for this chapter, named as sustainability survey (SS), the above-mentioned surveys with respect to the chapter's goal were considered to develop a customized instrument that combines various aspects of the previously noted instruments and newly created items to understand sustainability practices in the SEUS. These following sections outline the stages of development of the SS, along with the reliability and validity descriptions of this new instrument.

Classical Test Theory

Classical test theory (CTT) employs a conventional quantitative method to assess the reliability and validity of a scale based on its items (Cappelleri et al., 2014). CTT is founded on the notion that each observed score (X) is a combination of an underlying true score (T) and random error (E). Consequently, observed score (X) = true score (T) + error (E). True scores (which cannot be observed) define values for whatever is supposed to be measured, in this example, the relationship between individuals and sustainability. CTT assumes that item responses are coded so that higher response scores reflect a greater understanding of the concept of interest. Another assumption of CTT is that random errors are normally distributed (thus the expected value of random fluctuations is assumed to be 0) and uncorrelated to the true score (Crocker & Algina, 2008). Since this study is not testing the participant's knowledge but rather collecting information, only dimensionality component is measured, and item difficulty and item discrimination are not measured. Dimensionality, or the extent to which the items measure a hypothesized concept distinctly, can be evaluated through factor analysis. Exploratory factor analysis (EFA) is used to generate hypotheses about the structure of the data when there is uncertainty as to the number of factors being measured. It is also useful in determining items to remove because they contribute little to the presumed underlying factor or construct. EFA should be complemented by confirmatory factor analysis (CFA) in later stages of instrument development, by imposing the hypothesized structure from the EFA on new data to confirm that structure (Cappelleri et al., 2014). Both EFA and CFA are commonly used in the social sciences, particularly in psychology and sociology. The basic assumption of CFA is that the observed variables are a linear function of a set of latent variables. CFA begins by specifying a model that represents the relationships among the observed variables and the latent variables. This model is then tested against the data using a variety of fit indices and statistical tests to determine how well it explains the observed data. If the model fits the data well, it can be used to make inferences about the latent variables and the relationships among them. However, if the model does not fit the data well, it may need to be modified or a different model may need to be considered. This study utilizes EFA to explore the structure of the data and CFA to validate the structure.

Reliability

The concept of reliability refers to the consistency or stability of outcomes, i.e., if the assessment or data collection tool catches the same information in a consistent manner. Although tools or evaluations may be referred to as reliable, the term actually refers to the outcomes, not the tool itself. While results must be reliable, reliability alone is insufficient if they lack validity (Reynolds et al., 2010). There are several approaches for analyzing an instrument's reliability with a reliability coefficient when designing the instrument. Test-retest reliability, alternate-form reliability, and internal consistency reliability are all types of reliability coefficients (Reynolds et al., 2010). They are derived from the administration of the same test or tool on multiple occasions, administration of parallel forms of the instrument or test, and administration of a single test respectively. Internal consistency reliability is frequently used in quantitative research because they may be completed very rapidly and require just one administration of an instrument. Among estimations of reliability based on internal consistency, there are numerous prevalent statistical methods. Split-half reliability entails dividing a test or other instrument into two equal halves and administering each half separately. Using the Pearson product-moment correlation, the results of the first half are then correlated with those of the second half. Coefficient alpha or Cronbach's alpha (Cronbach 1951) and Kuder- Richardson Reliability (KR-20) (Kuder and Richardson 1937) are utilized more frequently. Both approaches analyze the consistency of a respondent's responses to all questions or a subset of an instrument. In other words, these estimations are comparable to the mean of all potential split-half coefficients.

Consequently, these estimates are susceptible to content heterogeneity, or the degree to which the instrument measures similar constructs (Reynolds et al., 2010). In this instance, if the underlying structure of an instrument is known to assess numerous constructs, these estimates are applied to items designed to test a particular construct. Then, a composite estimate of reliability is obtained. Typically, the reliability of composite scores is greater than that of the individual components (Reynolds et al., 2010). KR-20 is one of several reliability equations proposed by Kuder and Richardson (1937), which is one of the most often employed estimates. It is applicable when objects are scored as correct or incorrect (0 or 1). Cronbach's alpha (Cronbach 1951) is a broader variation of KR-20 that deals with things that can produce numerous values (0,1,2, etc.). As a result, coefficient alpha has become the most popular statistic for calculating reliability (Keith & Reynolds, 1990). This is especially true for surveys, which typically contain non-binary items. In general, researchers strive for a Cronbach's alpha value of 0.70 or above, however this value may be arbitrary. Cronbach's alpha has been criticized for being unconnected to the internal structure of the test and having minimal utility, despite its widespread use (Sijtsma, 2009). This study utilizes internal consistency reliability, specifically Cronbach's alpha as it deals with multiple constructs that produce numerous values to measure the reliability of the instrument.

Validity

Validity describes the closeness of what we intend to measure and what we measure i.e., accuracy of the interpretation of the score or result (Reynolds et al., 2010). One needs to measure both reliability and validity as reliable results do not necessarily lead to valid results (Reynolds et al., 2010). For understanding the survey instrument validity, one needs to calculate different types of validity: content validity, criterion-related validity, and construct validity (Reynolds et al., 2010). Content validity is defined as “the degree to which items in an instrument reflect the content universe to which the instrument will be generalized” (Straub, Boudreau et al. 2004). Content validity refers to the extent to which a test adequately samples the content area of a given construct. It is frequently reviewed based on the professional opinions of subject matter experts regarding the relevance of the content. Criterion-related validation is employed when a test user is looking to make inferences from test scores to examine behavior on a performance criterion that cannot be directly measured by a test. This typically breaks down into two types of criterion-related validation: predictive and concurrent. Predictive validity refers to the degree to which test scores predict criterion measurements that will be made in the future. For example, the SAT scores have some degree of predictive validity with respect to college grade point average (thus the justification for using SAT scores in making admissions decisions). Construct validation evidence is typically assembled through a series of studies. Correlational studies may be conducted to relate scores on a given test or instrument and some other measure of performance. Often multiple regression is used so that contributions of the construct of interest to variance in the criterion can be assessed in relationships to the contribution of other variables. Factor analysis is another approach that may be used to determine whether item responses cluster together in patterns that are reasonable when considering the theoretical structure of the chosen construct to provide evidence for or against validity (Crocker & Algina, 2008). For the development of this instrument content validity using expert opinions at the start of the development of the instrument and construct validity through factor analysis was used to measure validity.

Methods

In total, three surveys were created: a precursor survey, a pilot survey, and a main survey (the SS). The precursor interest survey was designed and distributed among Auburn and Opelika residents in the state of Alabama to select the seven most important SDGs to be evaluated. These selected seven SDGs acted as a basis for the pilot and the main survey construction. In the analysis of the pilot survey results, survey items relating to the awareness, knowledge, behavior, intended behavior, perception, concern about the seven selected SDGs from the precursor survey were analyzed using EFA. It was used to find the latent structure of items relating to these overlying themes or constructs. Based on the item loadings constructs were added and eliminated at this stage and the main survey (SS) was created. Finally, CFA was run to finalize the item loadings in their constructs – awareness/familiarity, concern/urgency, perception, involvement, behavior, and intended behavior about sustainability practices - identified after EFA. For clarity's sake, these constructs identified through factor analysis will be italicized (E.g., SDG-Awareness and Familiarity is a construct made up of correlated survey items relating to it, as identified through EFA).

Instruments

The precursor interest survey was based on an in-person interview where 30 participants from diverse backgrounds, age groups, occupations, and income levels were invited and interviewed. Based on the responses and comments from experts, the survey questions were created to rank the SDGs based on priority.

For the construction of the pilot survey instrument, we employed a three-stage strategy like McNeal, Walker, and Rutherford (2014) and multiple steps were taken to ensure validity and reliability of the survey instrument (Table 2.2). Stage 1 required the identification of salient scales to establish awareness, knowledge, concern, intent, intended behavior, and perceptions dimensions as they relate to SDGs. Stage 2 included the development and field testing of items internal to each of the awareness, knowledge, concern, intent, intended behavior, and perceptions scales established in Stage 1 and implementing any changes required. Stage 3 involved field testing each item followed by scale and item analyses and validation. The survey follows a similar structure and has two parts.

1. The first section asks respondents to self-report about their level of awareness, knowledge, concern, intent, intended behavior, and perceptions about sustainability in their neighborhood based on SDGs. It is from this section that we conducted EFA to explore items relating to specific factors/construct.

2. The second section consists of demographic questions about education, sexual orientation, age, location, occupation, gender, race, political affiliation, and income level.

Each process for each of the three stages mentioned above is as follows:

1. The salient scales were identified and developed using the below four steps.

a) Literature review associated with using survey instruments to understand the knowledge, attitude, perception, and practice about sustainability, SDGs, and policy development through citizen science (Afroz and Ilham 2020; Emanuel and Adams 2011; Melles 2019; Smaniotto et al. 2020). The purpose was to identify available survey instruments and gaps in knowledge.

b) Examine previously developed instruments for their awareness, knowledge, concern, intent, intended behavior, and perceptions dimensions scales that we could modify for our survey or that could be useful in informing the development of new scales.

c) Classify awareness, knowledge, concern, intent, intended behavior, and perceptions scales to ensure adequate coverage of all these dimensions.

d) Develop a set of preliminary scales to be reviewed by a panel of experts. The review was done by content experts (four university professors whose research is primarily in sustainability and resilience), survey experts (three researchers who are expert in creating surveys), and four students who are the prospective survey takers. The final scales were agreed upon based on their inputs.

2. Individual items for all the scales were created, adapting, altering, and adding items from previously published surveys and developing new items for the agreed upon dimensions. Demographic items, some of which are distinctive to this survey: education, sex, sexual orientation, income level, religion, political party affiliation, and occupation, among others were also created. Finally, the instrument was typed in Qualtrics for online distribution which was then distributed using Amazon Mechanical Turk (MTurk) (Buhrmester, Kwang, and Gosling 2016) to SEUS residents. The online instrument was pilot tested with professors and students from the department of geosciences in Auburn University to see if there are any errors in the layout, design, or data retrieval.

3. Field testing and analyses was a two-step process: (i) field testing with a sample of 250 to collect data to test the validity and reliability of the pilot survey instrument, to reduce the number of items in the pilot survey, to solicit feedback from a sample of respondents, and to determine how much time was required to complete the survey in order to finalize the instrument into the main survey instrument from which we could utilize for a larger-scale study and (ii) final collection of data after validity testing and removal of items that did not perform well to conduct CFA. Factor analysis was used to identify items that could be removed from the instrument to improve its factor structure, as well as an analysis of internal consistency reliability. Cronbach's alpha coefficient was used to quantify internal consistency in terms of item intercorrelation. To maximize alpha coefficients, items that are not significantly associated within their priori scale

were deleted, and data was reanalyzed until all items with low item–scale correlations were removed.

Survey Dissemination

Human subject research approval (AU IRB #22-138 EX 2204) was collected from university's institutional review board (IRB). The survey sample was a random sample drawn from voluntary participants from residents in the SEUS. The survey was available on the World Wide Web through Amazon MTurk and Qualtrics platform that allows for organized survey posting, data collection, and data download. Participants completed informed consent prior to completing the survey. The estimate survey sample of 1000 respondence was collected for further analysis.

Participants

The target audience for precursor survey was residents of Auburn-Opelika in Alabama and the pilot and the main survey were SEUS residents. The precursor survey was created with in-person group interview consisting of 30 participants consisting of 70% male and 30% female. The participants were recruited from different sustainability and environment groups in Auburn. The main survey was created based on the precursor survey and pilot survey refined with multiple iterations (discussed in Instrument section of Methods). The pilot and the main survey comprised of English-speaking SEUS residents. The pilot survey was distributed in May 2021 and collected a sample of 246 individuals. The pilot survey consisted of 41 questions with a total of 100 items. The participants for the pilot and the main survey were recruited from an online crowdsourcing system, MTURK, based on MTURK documentation of reliable performance completing other MTURK tasks. MTURK samples are representatively similar to traditional research subject pools in terms of race, gender, age, and education (Paolacci et al., 2010).

Workers were prescreened to ensure only those with good performance records will complete the survey. Workers were compensated for completing the study and compensation for task completion was within MTURK standards for similar tasks. The target of this study was to recruit 1,000 individuals. MTURK directed participants to the Qualtrics survey where they were asked to complete the multiple-choice based instrument and then provide basic demographic information (age range, gender, education level, income, etc.). Based on the analysis of pilot survey with 246 responses, the main survey was created removing some questions and changing the order of questions. As a result, the main survey consisted of 28 questions. This survey was conducted with the remaining sample of 739 individuals between July 6 and August 1, 2022. Individuals accessed the survey through MTurk. 1048 individuals attempted the survey out of which 358 were considered invalid as they were out of SEUS and submitted incomplete survey resulting in 690 valid responses. The total number of participants analyzed in this study was 936. Basic demographic information from all stages of the MTURK study can be found in Table 2.1.

Table 2.1: Demographic information of MTURK participants.

Category	Response	Pilot (n=246)	Main (n=690)	Total (n=936)
Gender	Male	135	287	422
	Female	111	447	558
	Non-binary	0	2	2
	Choose not to Identify	0	3	3
	18-25	19	56	75
	26-35	79	202	281
	36-45	63	189	252
	46-55	34	181	215

Age	55-65	26	71	97
	Over 65	18	40	58
	Choose not to respond	7	0	7
Education	Highschool	27	77	104
	Community College/Trade School	19	117	136
	Undergraduate Degree	114	266	380
	Graduate Degree	59	143	202
	Postgraduate and above	24	129	153
	Other	3	3	6
	Decline to state	0	4	4

Statistical Analysis

The statistical software suite used to analyze the data was Jamovi and R programming language. The data were used to develop, validate, and test reliability of constructs - awareness, knowledge, concern, intent, intended behavior, and perceptions scales. The pilot survey with 249 responses was used for EFA in Jamovi which was later combined with the 690 responses collected using the main survey for CFA in order to establish cross-validation. Cronbach's alpha, which is an estimate of internal consistency, was utilized to calculate reliability. Typically, most concept inventory researchers set 0.7 as the acceptable value for Cronbach's alpha (Nunally, 1978; Litwin, 1995). However, since concept inventories tend to not be homogenous tests, tests of internal consistency can seriously underestimate reliability (Miller, 1995). Due to this fact, some researchers have given 0.6 as the minimum acceptable value for the equivalent Kuder-Richardson 20 (Grolund, 1993; Anderson et al., 2002). To test the dimensionality of the concept inventory and understand how many latent factors were being measured, an EFA was completed using minimal residuals with varimax rotation in Jamovi. The goal of factor analysis is to figure out the variables' basic structure and, as a result, how strongly items load on a priori scale. With their own scale, all objects must load at least 0.45. (Walker and McNeal, 2013). For CFA diagonally weighted least squares (WLSMV) model is used in laavan module in R due to ordinal nature of the responses. Criterion pattern loading of .50 or higher was used to determine which items were loading onto which factors for all EFA for this study (Byrne, 2016). The model fit for CFA was measured by goodness-of-fit indices - the $\chi 2$ test of exact fit, the root mean squared error of approximation (RMSEA), standardized root mean squared residual (SRMR), Comparative Fit Index (CFI), and the Tucker–Lewis Index (TLI). Values of RMSEA and SRMR closer to 0 indicate better fit, values less than .08 considered acceptable fit (Kline 2016). For CFI and TLI values closer to 1 value indicate better fit, values greater than .90 indicate good fit (Hu and Bentler 1999).

Results

244 responses were recorded and analyzed to get the 7 selected SDGs from the precursor survey. These selected 7 SDGs acted as a basis for the pilot and the main survey construction (Figure 2.1).

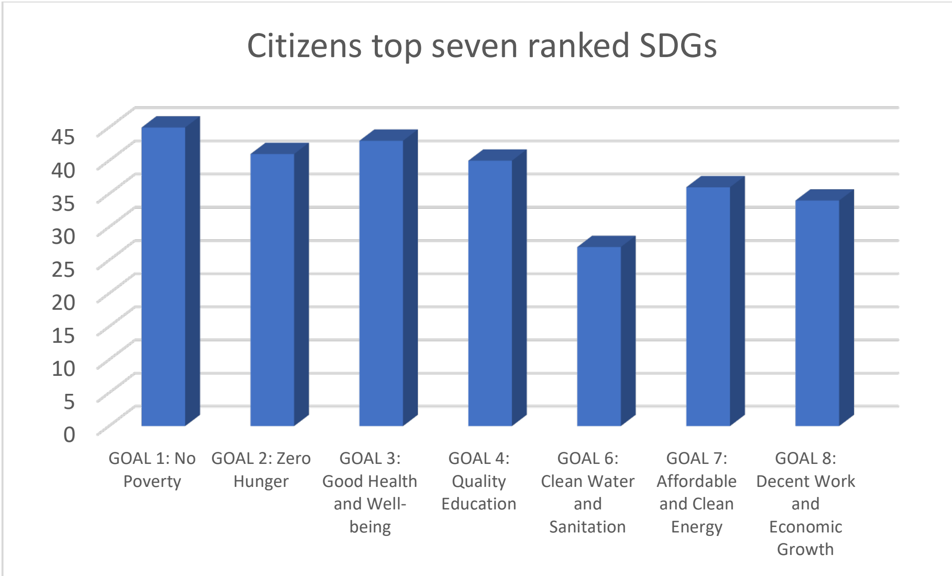

Figure 2.4: Precursor survey responses result

The pilot survey before EFA consisted of 43 questions with a median completion time of 11.4 minutes. Respondents answered questions about 1) awareness/familiarity about SDGs; 2) knowledge about SDGs; 3) concerns about attaining sustainability; 4) intent about supporting and practicing sustainability policies; 5) intended behavior about supporting and practicing sustainability policies; 6) perceptions about SDGs; and 7) demographics. Survey questions included a variety of types of items with multiple choice questions with Likert scale and yes/no responses (Table 2.2).

Table 2.2: Theoretical constructs that were examined during the exploratory factor analysis.

Criteria Name	**Purpose**	**Question numbers**	**Question Type**
SDG-Awareness and Familiarity	To understand if the participant is aware about sustainable development goal	Q1 to Q3	Likert Scale
SDG-Knowledge	To understand how much the participant know about sustainability and what falls under sustainable development goals	Q4 to Q11	Yes/No

SDG-Concern	To understand if the participant is concerned about the socioeconomic and environmental changes due to sustainability issues	Q12 to Q15	Likert Scale and Yes/No
SDG-Intent	To understand if the participant thinks or feels that the issues related to sustainability needs to be addressed	Q16	Likert Scale
SDG-Intended Behavior	To understand if the participant is ready to act to solve issues related to sustainability needs	Q17 to Q25	Likert Scale
SDG-Perception	To understand how the participant perceive about solving the issues related to sustainable development	Q26 to Q28	Likert Scale
No scale	Questions in general I am interested in knowing - not related to any scale	Q29 to Q30	
Demographics	General demographic question	Q31 to Q41	
Validity check		Q42	

These questions were subjected to EFA to develop the main survey, the Sustainability Survey. It was based on the strategy that only items with a moderate factor loading on their own scale and a low factor loading on other scales be kept. It also uses the intuitive-rational strategy, which says that only things that make sense to each other stay in the final instrument (Hase & Goldberg, 1967). After EFA the question structure changed based on the analysis.

Exploratory factor analysis (EFA)

Validity

Content validity was addressed in Stage 1 with a panel of experts, and in Stage 2 with a pilot test. Construct validity was investigated through minimum residuals with varimax rotation, Kaiser normalization, and Eigenvalues greater than one. The aim of factor analysis is to determine the basic structure of a set of variables to determine how strongly items load on a priori scale. That is, it is a method to determine if an item within a given scale is measuring that scale. Only items with a factor loading of at least 0.5 with their own scale and less than 0.5 with all other scales were kept. 15 “faulty” items were identified and removed. In addition to the loss of those 15 items the entire sub-scale of knowledge was lost due to low factor loading. Likewise, due to factor loadings, the Intended Behavior subscale and intent subscale was split into Behavior, Intended Behavior, and Involvement scale. In hindsight, this is likely due to the question stems that read: “I currently take specific action to make my community more sustainable with respect to achieving following goals.” (Behavior of present), and “I intent to take specific action to make my community more sustainable with respect to achieving following goals.” (Possibility of behavior in the future) in one set. In the end, the total number of questions in the refined scale was 28, decreased from the original 44. The 6 factors chosen in this study based on eigen value greater than 1.3 (Table 2.3) cumulatively explain 62.7% of the variances of the responses as shown in Table 2.4.

Table 2.3: Eigenvalues of the 6 factors in EFA

Initial Eigenvalues	
Factor	Eigenvalue
1	31.1779
2	9.5630
3	4.4035
4	3.4188
5	1.6281
6	1.3769

Table 2.4: Variance explained by the factors in EFA

Summary

Factor	SS Loadings	% of Variance	Cumulative %
1	16.59	19.52	19.5
2	14.22	16.73	36.2
3	10.30	12.12	48.4
4	6.25	7.35	55.7
5	3.72	4.37	60.1
6	2.20	2.59	62.7

Table 2.5 presents the factor loading for the different items to create the new scales. 'AQ' represents awareness/familiarity, 'CQ' represents concern, 'P' represents perception, 'I' represents intent, and 'IB' represents intended behavior on original items.

Table 2.5: Factor loadings of each item on 6 factors using 'Minimum residual' extraction method in combination with a 'varimax' rotation.

Items	Factor loadings					
	1	2	3	4	5	6
CQ4_1	0.728					
CQ4_10	0.585					
CQ4_11	0.642					
CQ4_12	0.629					
CQ4_13	0.606					
CQ4_14	0.594					
CQ4_2	0.671					
CQ4_3	0.64					
CQ4_4	0.715					
CQ4_6	0.557					
CQ4_7	0.553					
CQ4_8	0.578					
CQ4_9	0.565					
IQ1_1	0.673					
IQ1_2	0.657					
IQ1_3	0.715					
IQ1_4	0.703					
IQ1_5	0.712					

IQ1_6	0.629		
IQ1_7	0.695		
PQ1_1	0.675		
PQ1_2	0.68		
PQ1_3	0.71		
PQ1_4	0.639		
PQ1_5	0.687		
PQ1_6	0.636		
PQ1_7	0.678		
PQ2_1	0.597		
PQ2_2	0.666		
PQ2_3	0.707		
PQ2_4	0.575		
PQ2_5	0.643		
PQ2_6	0.558		
PQ2_7	0.624		
AQ3A_3		0.857	
AQ3A_12		0.85	
AQ3A_8		0.835	
AQ3A_9		0.833	
AQ3A_4		0.828	
AQ3A_7		0.822	
AQ3A_13		0.808	
AQ3A_6		0.801	
AQ3A_5		0.8	
AQ3A_17		0.799	
AQ3A_14		0.792	
AQ3A_2		0.781	
AQ3A_10		0.78	
AQ3A_1		0.771	
AQ3A_11		0.727	
AQ3A_15		0.723	
AQ3A_16		0.693	
AQ1		0.635	
AQ2		0.607	
IBQ6_2			0.805
IBQ6_1			0.803
IBQ6_7			0.794
IBQ6_4			0.767
IBQ6_6			0.762

IBQ6_3	0.743			
IBQ6_5	0.742			
IBQ8_1	0.707			
IBQ8_2	0.677			
IBQ8_3	0.654			
IBQ8_6	0.652			
IBQ8_7	0.643			
IBQ8_4	0.607			
IBQ8_5	0.584			
IBQ7	0.519			
PQ3_3		0.765		
PQ3_5		0.735		
PQ3_2		0.73		
PQ3_6		0.713		
PQ3_4		0.695		
PQ3_7		0.694		
PQ3_1		0.693		
IBQ1_1			0.699	
IBQ1_3			0.622	
IBQ1_5			0.604	
IBQ1_7			0.573	
IBQ1_2			0.572	
IBQ1_4			0.542	
IBQ1_6			0.526	
IBQ4				0.664
IBQ9				0.599
IBQ5				0.547

Note. 'Minimum residual' extraction method was used in combination with a 'varimax' rotation

Reliability

During the development of the SS, each scale was analyzed for internal consistency. Table 2.6 presents the alpha reliability for each refined scale. Of the 6 scales/sub-scales one was removed due to low reliability (alpha < 0.60) and 1 scale was rearranged into 3 other scales. The scale removed was the entire subscale of knowledge ($\alpha = 0.6$). Other items based on factor loadings were also removed resulting in 15 additional items being removed. The overall instrument reliability after the removal of poor items was $\alpha = 0.938$.

Table 2.6: Scale reliability using Cronbach's alpha coefficient.

Criteria Name	Final number of items	Alpha Reliability
Awareness/Familiarity (AW)	19	0.975
Concern/Urgency (CU)	34	0.965
Perception (P)	7	0.940
Behavior (B)	3	0.739
Involvement (I)	15	0.969
Intended Behavior – Engagement (IB_E)	7	0.938

Table 2.7 represents the new constructs and the number of items remaining in each construct after validity and reliability analyses.

Construct Name	Questions Selected from Jamovi (Varimax Rotation)	Number of questions
Awareness/Familiarity (AW)	Q1, Q2, Q3_1 - Q3_17	19
Concern/Urgency (CU)	Q15_1 to Q15_14 except Q15_5, Q16_1 – Q16_7, Q26_1 – Q26_7, Q27_1 – Q27_7	34
Perception (P)	Q28_1 to Q28_7	7
Behavior (B)	Q20, Q21, Q25	3
Involvement (I)	Q17_1 – Q17_7	7
Intended Behavior – Engagement (IB_E)	Q22_1 – Q22_7, Q23, Q241_Q24_7	15

Confirmatory Factor Analysis (CFA)

After running the reliability and validity test the main survey instrument was subjected to CFA in R to see how they perform with a bigger dataset. 1038 datasets were collected out of which 690 were added to already collected 249 responses to create a sample of 936 responses for

CFA. In a CFA analysis, the null hypothesis is that the matrix inferred by the data and model is statistically identical to the input or analysis matrix. Hence, overall "fit" in our study refers to how accurately the given model can replicate the original polychoric correlation analysis matrix i.e., that the two matrices are statistically equivalent. It is important to note that the analysis used in this study employed robust approaches, which are typically needed for ordinal data and produces various scaled statistics. At the p =.05 significance level, the scaled (robust) chi-square for our model was X2(df) = 13610.26 (3470). This resulted in rejecting the null hypothesis which means there is no relationship between the factors created. Due to chi square being sensitive to sample size and given the large sample size in this dataset, even small departures are significant, leading to a need of calculating other fit indices providing better analysis pathways.

The root mean square error of approximation (RMSEA) is a popular measure of the difference between the model-based correlation matrix and the observed correlation matrix providing data to understand model fit. It makes modifications based on model complexity (parsimony-adjusted) and has a known sample distribution, allowing confidence intervals to be calculated. The scaled RMSEA values obtained from lavaan output in R were 0.058. For analysis purpose an RMSEA <=.05 as the threshold for a close fit; RMSEA =.05 –.08 as a reasonable fit; and RMSEA >=.10 as a poor fit. On the basis of the obtained RMSEA point estimate =.058 and the 90% CI [.057,.059], we determined that the model's fit was satisfactory.

The other two popular fit measures utilized in this study to assess model adequacy were — the Comparative Fit Index (CFI) and the standardized root mean square residual (SRMR). The CFI is a member of the incremental fit index family that compares your model to a constrained baseline model. The SRMR is derived from the real differences (discrepancies) between model-based correlations and actual correlations. In addition, various interpretation recommendations for these measures have been presented. For this case, the threshold parameters were CFI >= 0.91 and SRMR <= 0.08. Based on the thresholds, we determined that CFI.scaled =.941 and SRMR =.007 provided additional evidence that the model was credible.

Based on the values of fit measures, it was concluded that the model was plausible. Finally, item parameter estimates were examined from lavaan output are shown in Table 2.8.

Table 2.7: Laavan output of CFA and item loadings

	Item	Standardized	ci.lower	ci.upper	SE	Z	p.value
1	AW1	0.82	0.798	0.842	0.011	73.375	0
2	AW2	0.809	0.785	0.834	0.012	65.323	0
3	AW3a	0.888	0.874	0.902	0.007	122.299	0
4	AW3b	0.914	0.902	0.927	0.006	145.515	0
5	AW3c	0.927	0.916	0.937	0.005	175.576	0
6	AW3d	0.942	0.933	0.95	0.005	206.838	0
7	AW3e	0.901	0.887	0.915	0.007	126.34	0
8	AW3f	0.905	0.891	0.919	0.007	126.855	0
9	AW3g	0.913	0.901	0.926	0.006	147.555	0
10	AW3h	0.925	0.915	0.935	0.005	181.019	0
11	AW3i	0.936	0.927	0.946	0.005	199.235	0
12	AW3j	0.896	0.882	0.909	0.007	130.573	0
13	AW3k	0.866	0.85	0.882	0.008	107.305	0
14	AW3l	0.922	0.912	0.933	0.005	167.782	0
15	AW3m	0.916	0.905	0.927	0.006	162.294	0
16	AW3n	0.857	0.84	0.874	0.009	100.201	0
17	AW3o	0.867	0.852	0.882	0.008	112.25	0
18	AW3p	0.826	0.805	0.847	0.011	77.947	0
19	AW3q	0.913	0.902	0.924	0.006	161.421	0
20	CU1a	0.631	0.588	0.674	0.022	28.839	0
21	CU1b	0.693	0.656	0.73	0.019	36.608	0
22	CU1c	0.601	0.554	0.649	0.024	24.901	0

23	CU1d	0.668	0.63	0.707	0.02	33.913	0
24	CU1e	0.624	0.58	0.667	0.022	28.137	0
25	CU1f	0.77	0.738	0.802	0.016	47.149	0
26	CU1g	0.737	0.703	0.771	0.018	41.908	0
27	CU1h	0.726	0.691	0.761	0.018	40.919	0
28	CU1i	0.754	0.722	0.787	0.017	45.667	0
29	CU1j	0.733	0.7	0.766	0.017	43.297	0
30	CU1k	0.744	0.712	0.776	0.016	45.216	0
31	CU1l	0.75	0.718	0.781	0.016	46.308	0
32	CU1m	0.735	0.701	0.769	0.017	42.228	0
33	CU2a	0.794	0.767	0.822	0.014	56.349	0
34	CU2b	0.778	0.748	0.807	0.015	51.819	0
35	CU2c	0.802	0.774	0.829	0.014	56.781	0
36	CU2d	0.768	0.737	0.799	0.016	48.251	0
37	CU2e	0.776	0.746	0.805	0.015	51.366	0
38	CU2f	0.782	0.754	0.811	0.015	53.668	0
39	CU2g	0.78	0.75	0.81	0.015	50.647	0
40	CU3a	0.826	0.801	0.851	0.013	65.904	0
41	CU3b	0.809	0.781	0.836	0.014	57.675	0
42	CU3c	0.817	0.791	0.844	0.014	60.423	0
43	CU3d	0.781	0.75	0.811	0.016	50.316	0
44	CU3e	0.797	0.77	0.824	0.014	58.037	0
45	CU3f	0.808	0.781	0.835	0.014	59.18	0
46	CU3g	0.749	0.716	0.782	0.017	44.456	0
47	CU4a	0.775	0.746	0.804	0.015	52.712	0
48	CU4b	0.749	0.717	0.781	0.016	46.168	0
49	CU4c	0.774	0.744	0.804	0.015	50.293	0
50	CU4d	0.701	0.663	0.738	0.019	36.438	0
51	CU4e	0.751	0.72	0.782	0.016	47.149	0
52	CU4f	0.755	0.724	0.786	0.016	47.423	0
53	CU4g	0.73	0.696	0.764	0.017	41.971	0

54	IB_E1a	0.866	0.848	0.883	0.009	96.027	0
55	IB_E1b	0.896	0.881	0.911	0.008	116.633	0
56	IB_E1c	0.899	0.883	0.915	0.008	111.252	0
57	IB_E1d	0.855	0.835	0.876	0.011	80.892	0
58	IB_E1e	0.856	0.837	0.875	0.01	89.676	0
59	IB_E1f	0.876	0.859	0.893	0.009	100.696	0
60	IB_E1g	0.872	0.854	0.89	0.009	97.357	0
61	IB_E2	0.599	0.55	0.648	0.025	23.88	0
62	IB_E3a	0.88	0.863	0.897	0.009	101.165	0
63	IB_E3b	0.905	0.89	0.921	0.008	117.255	0
64	IB_E3c	0.897	0.88	0.914	0.009	103.323	0
65	IB_E3d	0.828	0.803	0.852	0.012	67.251	0
66	IB_E3e	0.872	0.852	0.891	0.01	89.246	0
67	IB_E3f	0.87	0.851	0.89	0.01	87.65	0
68	IB_E3g	0.861	0.841	0.881	0.01	84.429	0
69	I1a	0.869	0.847	0.891	0.011	77.076	0
70	I1b	0.868	0.846	0.889	0.011	79.273	0
71	I1c	0.897	0.879	0.915	0.009	96.017	0
72	I1d	0.843	0.816	0.869	0.014	62.423	0
73	I1e	0.877	0.857	0.896	0.01	89.692	0
74	I1f	0.904	0.884	0.923	0.01	90.51	0
75	I1g	0.899	0.881	0.916	0.009	99.101	0
76	P1a	0.849	0.821	0.877	0.014	58.768	0
77	P1b	0.865	0.839	0.89	0.013	66.703	0
78	P1c	0.911	0.888	0.934	0.012	77.213	0
79	P1d	0.881	0.854	0.908	0.014	64.108	0
80	P1e	0.825	0.796	0.854	0.015	55.596	0
81	P1f	0.852	0.824	0.88	0.014	59.476	0
82	P1g	0.849	0.823	0.875	0.013	63.275	0
83	B1	0.605	0.542	0.669	0.033	18.603	0
84	B2	0.96	0.896	1.023	0.032	29.668	0

85	B3	0.692	0.636	0.748	0.029	24.016	0

This output presents the standardized factor loadings and their standard errors for the 85 items on the Awareness/Familiarity (AW), Concern/Urgency (CU), Perception (P), Behavior (B), Involvement (I), and Intended Behavior – Engagement (IB_E) latent variables of the instrument. These results support the conclusion that the instrument retained its structure with the new items of the instrument. The loadings ranged from 0.8 to 0.95 for awareness/familiarity, from 0.6 to 0.83 for concern/urgency, from 0.599 to 0.899 for intended behavior-engagement, from 0.84 to 0.91 for involvement, from 0.8 to 0.92 for perception, and from 0.6 to 0.97 for behavior, indicating that the magnitude of the item-factor relationships was adequate with cutoff for acceptable loadings being 0.5. Loadings offer researchers vital information; they indicate how much item scores vary with a one-unit change in the construct. Items with greater loadings are more sensitive to changes in levels of the latent construct they measure and contribute more to defining the construct than items with lower loadings. Item R2s, also known as squared multiple correlations or SMCs, are related to factor loadings. R2s are the squared standard loadings of items; they represent the proportion of variance explained by each factor for each item related to the factor. The greater the amount of an item's variance that is explained by the factor, the more accurately the item measures the factor. The R2 values vary between 0.36 and 0.93 for all their items with respect to their scale. There is no specific threshold for acceptable R2s but values greater than 0.50 are desired and higher values are preferable. Only nine items had R2 values less than 0.5.

This large sample CFA of the SS offers evidence to the construct measurement validity of the scales in the SS. While the objects' relationships with their respective constructs differ, they appear to perform well as a whole.

Discussion

This study has developed and validated a new survey instrument called the SS (see Appendix A), which collects information on residents' awareness/familiarity, concern/urgency, perception, behavior, involvement, and intended behavior regarding sustainability practices in their neighborhood based on the UN SDGs. The SS was created by drawing from previous instruments related to sustainability and SDGs and was tested in the field with a total of 936 responses. Through analysis of data from 246 pilot participants, 15 items were identified and eliminated with either low factor loading or low internal consistency reliability. The original 100-item pilot survey was refined to a new instrument, the SS, that measures 1) awareness/familiarity about SDGs; 2) concern/urgency about SDGs; 3) involvement in supporting and practicing sustainability policies; 4) intended engagement in supporting and practicing sustainability policies; 5) perceptions of SDGs; 6) behavior supporting sustainability practices; and 7) demographic information of SEUS residents in their city. This survey can be used by researchers to determine the knowledge and values of residents about sustainability policies in their area.

Limitations

As with any research-grade survey, the reliability and validity of the SS may be limited when considering future populations under investigation. Sub-scales with low numbers of items may need to be combined into larger scales or additional items may need to be added in future studies. Nevertheless, diligent investigators using the SS in future studies should be able to measure sustainability awareness/familiarity, concern/urgency, involvement, perception, intended behavior, and behavior in greater detail than previous research. These findings will enable policy makers to gain a better understanding of which policies will be accepted and where additional efforts are required for education campaigns or marketing strategies.

Conclusion

In conclusion, the development and validation of the SS represents a significant contribution to the field of sustainability research. The SS provides a detailed and comprehensive measurement tool for researchers to assess residents' awareness/familiarity, concern/urgency, perception, behavior, involvement, and intended behavior about sustainability practices in their neighborhood based on UN SDGs. While the survey has limitations, such as the need for future validation with different populations and potential refinement of sub-scales, the SS provides a valuable tool for researchers and policymakers to better understand the attitudes and behaviors of residents towards sustainability policies. As such, the SS can help inform the development and implementation of effective education campaigns and marketing strategies to promote sustainable practices and achieve the UN SDGs.

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CHAPTER 3: GROUP DIFFERENCES IN SUSTAINABILITY SURVEY RESPONSES AND THEIR RELATIONSHIPS BETWEEN CONSTRUCTS: A STRUCTURED EQUATION MODELING APPROACH

Introduction

According to Lew et al. community development has always focused on sustainability as a core concept while emphasizing conservation and mitigation (Lew et al. 2016). Hence, thinking about sustainability as a community effort is an important first step in achieving sustainability. In this chapter, the responses collected to validate the survey instrument, the SS, in the chapter 2 were analyzed to address the following questions: 1) What motivates the community to engage in sustainability efforts? 2) Are there any notable differences between various demographic groups in their attitudes towards sustainability? 3) Do the identified motivating factors have any relationships between them, and can they influence or dictate the acceptance and adoption of sustainability practices as a community effort? In order to address these questions, the chapter focuses on exploring the differences in SEUS residents' awareness/familiarity, concern/urgency, perception, behavior, involvement, and intended behavior about sustainability practices in their neighborhood based on the UN SDGs. This investigation is further explored using multigroup confirmatory factor analysis (MGCFA) to understand how different demographic groups identify with the subject matter and structural equation modeling (SEM) to prove the hypothesis that involvement, behavior, and intended behaviors about sustainability practices can be predicted by awareness/familiarity, concern/urgency, and perception about UN SDGs.

Multigroup CFA (MGCFA)

As explained in Chapter 2, CFA is a statistical technique used to test the measurement structure of a set of variables. One of the key advantages of CFA is its ability to test the measurement structure of a set of variables with multiple indicators. This means that the model can account for the fact that a single latent variable can be measured by multiple observed variables, and that these observed variables may be correlated with each other. Additionally, CFA allows for testing of the measurement equivalence or measurement invariance, meaning that the factor structure is the same across different group using MGCFA with nested model comparison (Vandenberg and Lance 2000). Meaningful comparisons of relationships and means are impossible to perform without first establishing measurement equivalence (Billiet et al. 2003). Researchers frequently use MGCFA to conduct such comparison between all different kinds of groups; for example, on teachers' acceptance on use of a technology (Leem and Sung 2019), on political trust (André 2014), on energy policy acceptance (Steg, Dreijerink, and Abrahamse 2005), on sustainable transportation (Jakovcevic and Steg 2013), on marine restoration (O'Connor et al. 2021), on environmental concerns (Mayerl and Best 2019), on sustainable production (Naspetti et al. 2017), and attitude towards sustainable development (Biasutti and Frate 2017). It is established when the difference in model parameters between groups are so small that it can be attributed to chance (Hoyle and Smith 1994; Wu, Li, and Zumbo 2007) and can be claimed that any changes in factor scores are related to group characteristics, as opposed to model, or inventory flaws making comparisons appropriate (Brown et al. 2015).

Most research distinguishes and tests three types of equivalencies or invariance: configural equivalence, metric equivalence, and scalar equivalence (Steenkamp and Baumgartner 1998). Configural equivalence is established if a factor model fits the data well across all groups (the same items load on the same latent factor(s)). This is the lowest equivalency level. For configural invariance, an RMSEA of less than .05 is recommended (Wu, Li, and Zumbo 2007).

Then, metric equivalency must be determined which denotes that the factor loadings of the items and their meanings are equivalent across groups (Davidov 2009). This implies that a one-unit increase in the measurement scale of the latent variable has the same significance across all groups (Meuleman, Davidov, and Billiet 2009) and is established if the change in CFI is small (i.e. $\Delta CFI \leq .01$) (Cheung and Rensvold 2002). The highest level of invariance is scalar invariance, which indicates that intercepts across groups are equal. Scalar equivalence implies that we can compare means across groups and, therefore, rank groups according to different factors (Meredith 1993; Steenkamp and Baumgartner 1998) and is indicated if $\Delta CFI \leq .01$(Cheung and Rensvold 2002).

These structures are theoretical but can be difficult to achieve with real world data. Hence, partial invariance is modeled to allow investigating measurement equivalence by assuming that some but not all parameters of the factor structure are invariant across groups. Specifically, the partial invariance model (PIM) allows for the identification of groups that have similar factor structure, while also allowing for some degree of variation in the factor structure across groups. This model is particularly useful when testing for measurement equivalence across different cultural or linguistic groups. As noted by (Vandenberg and Lance 2000), "it is often more practical to relax complete invariance constraints and to look for a model that is at least partially invariant" (p. 132). The PIM thus provides a more nuanced and flexible approach for evaluating measurement equivalence across groups, as compared to other models such as the strict invariance or configural invariance models.

Structural equation models (SEM)

CFA precedes SEM which is used to specify structural relationships (e.g., regressions) among the latent variables (Moore 2012). SEM is a statistical technique that combines the concepts of confirmatory factor analysis and multiple regression analysis to test complex hypotheses about relationships among multiple variables. SEM allows researchers to test hypotheses about both the measurement structure of the variables and the relationships among them. It is commonly used in fields such as psychology, sociology, and education to test hypotheses about the underlying structure of theoretical models. SEM consists of two models: (1) the measurement model, which specifies the number of factors, the links between indicators and factors, and the connections among indicator error relationships. (i.e., a CFA model); and (2) the structural model, which specifies how the various factors are related to one another (e.g., direct or indirect effects, and relationship). When a poor model fit is observed in SEM research, it is more likely to be the result of misspecification in the measurement model component than the structural component. This is because the measurement model is typically more susceptible to errors than the structural model (e.g., problems in the selection of observed measures, mis specified factor loadings, additional sources of covariation among observed measures that cannot be accounted for by the specified factors). Before estimating and interpreting the structural relationships between latent variables, an adequate measurement model must be created, even though CFA is not the key analysis in SEM investigations.

SEM are most often represented graphically. Figure 3.1 is a graphical representation of the structural equation model used in this study:

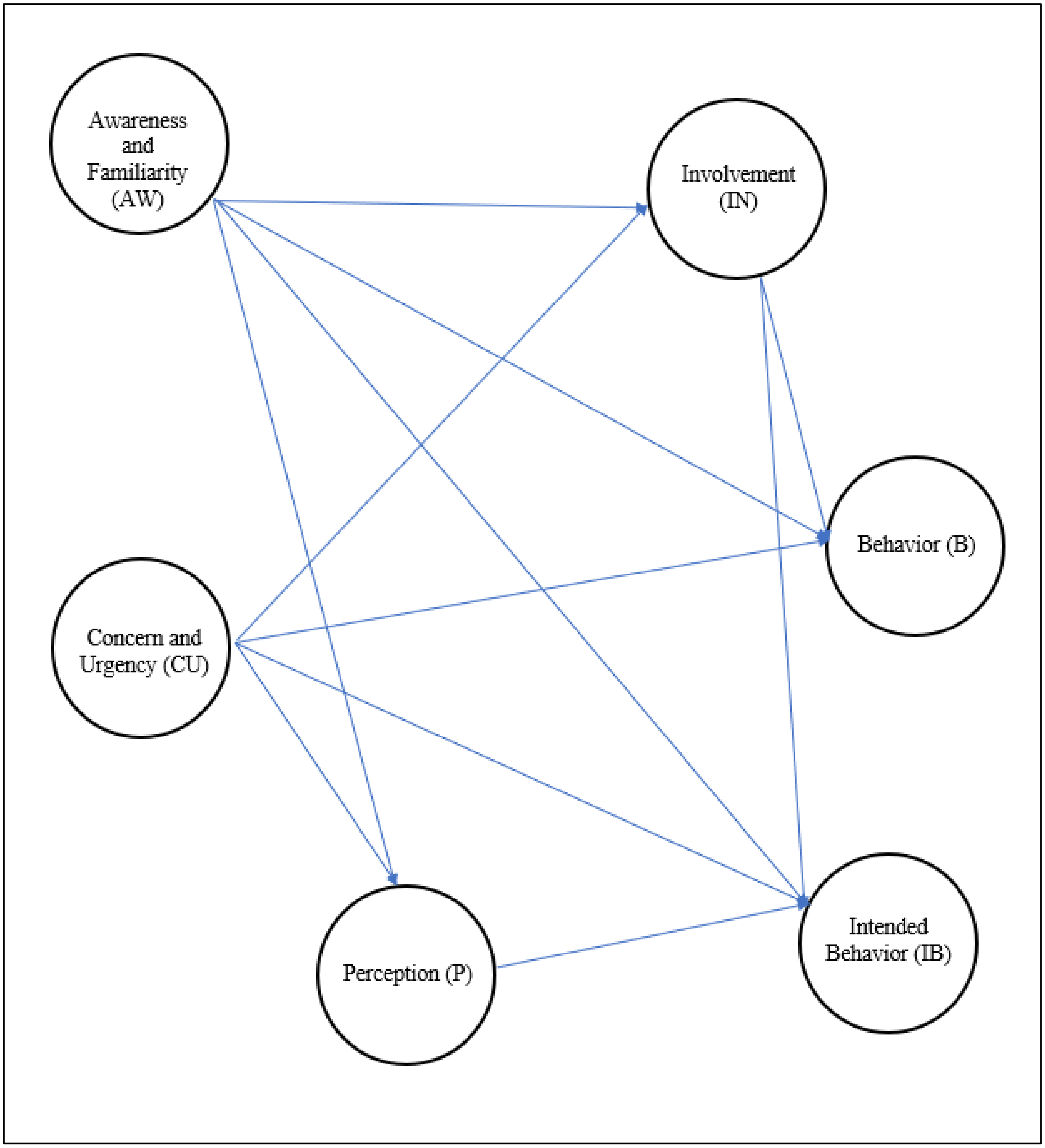

Figure 3.5: Graphical representation of SEM Model

MGCFA and SEM Hypotheses

MGCFA model

In this chapter we are comparing the constructs – awareness/familiarity, concern/urgency, intended behavior, perception, and involvement among three demographic groups – income level, gender, and political affiliation. The following hypothesis was adapted for the multigroup CFA analysis.

Hypothesis 1: Females will score higher on all 5 sustainability constructs compared to males.

Hypothesis 2: Liberals will score higher on all 5 sustainability constructs compared to conservatives.

Hypothesis 3: Individuals with high income levels will score higher on all 5 sustainability constructs compared to individuals with low-income levels.

The above group differences are tested through responses collected by the SS in chapter 2 measuring awareness/familiarity, concern/urgency about sustainability issues, perceptions about sustainability policies, intended behavior towards sustainability and involvement with sustainability policies using a Likert scale.

Theories behind multigroup CFA

Previous studies have found that females generally exhibit greater environmental concern and engagement in pro-environmental behaviors compared to males (Li, Wang, and Saechang 2022; Vicente-Molina, Fernández-Sainz, and Izagirre-Olaizola 2018; Zhao et al. 2021). This gender difference has been attributed to a range of factors such as differences in environmental values, socialization, and perceived responsibility for environmental issues.

Political ideology has also been found to be a strong predictor of environmental attitudes and behaviors, with liberals generally exhibiting more positive attitudes and behaviors towards sustainability than conservatives (Nawrotzki 2012; P. W. Schultz et al. 2004). This ideological difference has been attributed to differences in values, worldviews, and socialization.

Similarly, there is some evidence that higher income levels may be associated with greater environmental concern and engagement in pro-environmental behaviors (Helliwell et al. 2018; Lorek and Spangenberg 2014). This association has been attributed to a range of factors such as greater access to environmental information, resources, and opportunities to engage in pro-environmental behaviors. However, the relationship between income and sustainability attitudes and behaviors is complex and may vary depending on contextual factors.

SEM model

In this chapter we test the relationship between SEUS residents' awareness/familiarity, concern/urgency, perception, behavior, involvement, and intended behavior about sustainability practices in their neighborhood based on UN SDGs. The following hypotheses were adapted for the SEM analysis.

Hypothesis 1: Individuals who are more aware of sustainability issues and are more concerned about them will be more involved with sustainability policies.

Hypothesis 2: Individuals who are more aware of sustainability issues and are more concerned about them will have better perception of sustainability issues and policies.

Hypothesis 3: Individuals who are more aware, concerned, and involved with, engage in behaviors related to sustainability issues.

Hypothesis 4: Individuals who are more aware, concerned, involved with behaviors related to and perceive the relevance of sustainability issues will be more likely to intend to continue engaging in those behaviors.

These hypotheses are tested by using CFA and SEM based on the responses collected through the SS from chapter 2. The survey measured involvement with sustainability issues, current behavior related to sustainability, perception of relevance of sustainability, awareness about sustainability issues, concern about sustainability, and intended behavior related to sustainability using a Likert scale which examined the measurement structure of the variables and the relationships among them by testing for the robustness of the model.

Theories behind relationships between the variables in question

There are several theories suggesting relationships between the different constructs used in this study. There are two theories which study human behavior related to awareness, concern, perception, and involvement: protection motivation theory (PMT) and elaboration likelihood model (ELM). The theory of the PMT suggests that when individuals are aware of an issue and are concerned about it, they are more likely to perceive the issue as a potential threat and to take steps to protect themselves from the potential consequences of that issue (Chenoweth, Minch, and Gattiker 2009; Tsai et al. 2016; Milne, Sheeran, and Orbell 2000). In other words, when individuals are motivated to safeguard themselves from an issue, they are more likely to get involved with it. ELM also suggests that when individuals are aware of an issue and concerned about its implications, they are more likely to engage with the information about it and become involved. Hence, the theory suggests that when people elaborate on the information, they are more likely to perceive the issue as personally relevant to themselves or their interests (Lange, Kruglanski, and Higgins 2011; J. Kitchen et al. 2014; Dillard and Shen 2013; Cole et al. 1990; Meng and Choi 2019). Therefore, the level of elaboration, or the extent to which people process the information, plays a crucial role in determining their involvement with the issue, according to the ELM. In summary, concern, awareness and perception are crucial in shaping involvement with an issue. Theories like PMT and ELM suggest that when individuals are aware of an issue and are concerned about it, they are more likely to perceive the issue as relevant to themselves or to their interests, and therefore become more involved with it.

In this research, involvement and intended behavior are related but distinct constructs. Involvement refers to the degree to which an individual perceives an issue to be relevant to themselves or to their interests and engages with it, while intended behavior refers to an individual's intentions or plans to engage in a particular behavior in response to an issue.

Peer-reviewed literature has found that involvement is positively associated with intended behavior. For example, a study published in the journal "Health Psychology" found that involvement in health-related issues was positively associated with intentions to engage in health-promoting behaviors. The study surveyed a sample of individuals and found that those who were more involved in health-related issues were more likely to have intentions to engage in behaviors such as exercising and eating a healthy diet (Weinstein, Rothman, and Sutton 1998). Another study, published in the journal "Journal of Environmental Psychology", found that involvement in environmental issues was positively associated with intentions to engage in pro-environmental behaviors. The study surveyed a sample of individuals and found that those who were more involved in environmental issues were more likely to have intentions to engage in behaviors such as recycling and conserving energy (P. Schultz and Zelezny 1998). These studies suggest that involvement is a key predictor of intended behavior. When individuals are more involved with an issue, they are more likely to have intentions to take actions to address it.

The theories behind perception, involvement, and behavior leading to intended behavior utilized in this study are theory of planned behavior (TPB) and theory of self-determination. TPB suggests that when individuals perceive an issue as relevant, are involved with it and engage in behaviors related to it, they are more likely to form intentions to continue engaging in those behaviors. According to the TPB, intentions to engage in a behavior are determined by three factors: attitudes towards the behavior, subjective norms, and perceived behavioral control. When individuals perceive that a behavior will lead to positive outcomes, perceive social pressure to continue the behavior, and perceive that they have control over the behavior, they are more likely to form intentions to continue engaging in the behavior (Meng and Choi 2019; Conner and Armitage 1998; Conner 2020; Bosnjak, Ajzen, and Schmidt 2020; White Baker, Al-Gahtani, and Hubona 2007). The theory of self-determination suggests that when individuals perceive that an issue is relevant to their values and goals, and they have autonomy and competence in the situation, they are more likely to form intentions to continue engaging in the behavior. The theory of habit formation suggests that when individuals engage in a behavior repeatedly and consistently, they are more likely to form intentions to continue engaging in that behavior, as it becomes a habit (Deci, Olafsen, and Ryan 2017; Vansteenkiste, Niemiec, and Soenens 2010; Gagne et al. 2018).

In summary, theories like PMT, ELM, TPB, self-determination and habit formation suggest that when individuals who perceive an issue as relevant resulted due to their awareness and concern about the issue, are involved with it, and engage in behaviors related to it. These intentions are important as they provide guidance and direction for future actions.

Methods

Survey Instrument

In this study, the survey developed and validated in the previous chapter was used. The survey format is akin to McNeal, Walker, and Rutherford's approach (McNeal, Walker, and Rutherford 2014), consisting of two parts.

1. The first part of the survey prompts the respondents to report their individual levels of awareness/familiarity, concern/urgency, involvement, intended behavior, and perceptions about the SDGs and sustainability policies within their locality. This section also seeks to obtain information about the behavior of respondents regarding supporting sustainability practices.
2. The second section of the survey contains demographic questions related to the respondent's age, gender, race, occupation, income level, education, political affiliation, sexual orientation, and geographic location.

Data collection

As explained in Chapter 2, once the institutional review board (IRB) approved the non-human subject research (22-138 EX 2204), the survey was made available on the World Wide Web through Amazon MTurk and Qualtrics platforms. Precursor survey was conducted to find the top 7 SDGs relevant for Auburn/Opelika residents which was the basis of the survey created. In total, 936 responses were collected and analyzed for the study in two stages - pilot survey and main survey. Pilot survey responses (n=246) were used for EFA which resulted in the main survey (n=690) consisting of 28 questions with a total of 92 items after removing all the incomplete, duplicate, and outside of SEUS responses. Responses that did not fulfil the validation check of 2+4 were also eliminated. (Appendix A). Portion of demographic data collected from MTurk used in MGCFA are available in Table 3.1.

Table 3.8: Demographic information of MTURK participants used for MGCFA. Values in parentheses indicate percent.

Category	**Response**	**Total (n=936)**
	Male	379(40.49)

Gender	Female	552(58.97)
	Non-binary	2(0.2)
	Choose not to Identify	3(0.3)
Income	<25000	173 (18.48)
	25000 – 49,999	287 (30.66)
	50,000 – 69,999	276 (29.48)
	70,000 – 99,999	148 (15.81)
	>100,000	52 (5.55)
Political affiliation	Very liberal	220 (23.51)
	Somewhat liberal	170 (18.16)
	Neutral	204 (21.79)
	Somewhat conservative	186 (19.87)
	Very conservative	156 (16.66)

Content validity and construct validity were established through EFA and reinforced through CFA. A total of 936 responses resulted a CFA model with a scaled (robust) chi-square value of X2(df) = 13610.26 (3470) at the p=.05 significance level, the scaled RMSEA value was 0.058, CFI.scaled was .941 and SRMR was .07, indicating that the model was credible.

Additionally, items in the model had acceptable loadings of 0.5 or higher to their respective constructs, further supporting the model's fit. Finally, the CFA models were also analyzed for each demographic group, as identified in Table 3.1, to explore measurement invariance and examine potential differences in responses to further analyze their relationship with sustainability policy acceptance.

Modeling procedure

Statistical Analysis of SEM

Laavan package in R (Oberski 2014) is used to perform multigroup analysis and SEM. Three demographic subgroups: Gender, Political affiliation, and Income level, were compared. Gender was divided into two groups – male and female; non-binary and chose not to identify any one group, were ignored as there were not enough responses in those subgroups. Political affiliation was also divided into two groups – conservative and liberal. Conservative population was created by combining very conservative and somewhat conservation/right leaning. Liberal population was created by combining very liberal/progressive and somewhat liberal/left leaning. Middle of the road responses were ignored due to low responses rate for this option. Similarly, income level was also divided into two sub-groups – below 50,000 and above 50,000 yearly incomes. This cutoff was chosen based on the American Economic Class system where the cutoff of lower-middle class is 53,413 and is rounded to 50,000 for this study (Snider and Kerr 2022). For SEM model, all the population collected (n=936) was taken into consideration.

The analyses of invariance were conducted in all the subgroups mentioned above. There are five latent variables analyzed – awareness/familiarity, concern/ urgency, perception, involvement, and intended behavior-engagement. The latent variable – behavior was not taken into consideration for MGCFA because of smaller number of items as compared to other variable, and smaller number of responses in the group resulting in negative variance for MGCFA. Awareness/familiarity has 19 items, concern/urgency has 34 items, perception has 7 items, involvement has 15 items, and intended behavior has 7 items (Table 2.6). 5-factor model in Laavan was applied. The measeqsyntax function was utilized to compare the fit of each group model to the overall model. The measeqsyntax function allows for the specification of multigroup models with ordered categorical indicators, which is ideal for the survey data collected with 5-scale Likert scale responses. First, the model was specified by defining the factor loadings for each item on their respective factors. Then this model was used as the baseline for the multigroup analysis for each demographic group identified in the survey (based on Table 3.1), allowing for the examination of potential differences in the responses to further analyze their relationships with sustainability policy acceptance. The same factor structure for each group was specified, but different thresholds, factor loadings, and item intercepts were allowed, indicating that the relationships between the factors and their respective items may differ across groups. The ordered = TRUE specifies that the items in the model are ordinal, meaning that they have ordered categories that correspond to increasing levels of the latent variable. The parameterization = "delta" specifies that the parameterization used for the ordinal items is the delta parameterization, which estimates the thresholds for each item and assumes that they are equal across groups. The ID.fac = "std.lv" specifies that the identification of the model is based on the standardized factor loadings, which is a common identification strategy for confirmatory factor analysis. The ID.cat = "Wu.Estabrook.2016" specifies the estimation method for the categorical data, which is the WLSMV (Weighted Least Squares Means and Variance adjusted) estimator with the Satorra-Bentler chi-square test statistic (Xia, Yung, and Zhang 2016). This method is appropriate for ordinal data and accounts for the non-normality of the data. Finally, the group command and group.equal command was used to specify the grouping variable and the type of equality constraint used for the respective model. Example: the groups can be defined by political affiliation and the group.equal can be defined by the configural which assumes that the factor structure to be equal across groups. The group.equal command is written as loadings, intercepts, and thresholds to specify metric and scalar models for each demographic group respectively.

The model fit was evaluated and compared using the lavTestLRT function - the root means square error of approximation (RMSEA; ((Browne and Cudeck 1992)); the comparative fit index (CFI; (Bentler 1990); and the Tucker–Lewis index (TLI test; (Bentler 1990). A good fit is indicated by CFI and TLI values close to 0.95 and RMSEA values under 0.08. With ΔCFI 0.01 and prchisquare >= 0.05, measurement invariance suggests a good fit (Hu and Bentler 1999). In the first step, the full parameter invariance was tested, i.e., the respective parameter matrices were constraint to be identical across all groups (e.g., group A = group B). If this step causes a significant increase in chi-square ($\Delta\chi 2$), the information from modification indices was used to relax the constraints of the parameter with the highest modification index (Byrne, Shavelson, and Muthén 1989; Marsh and Hocevar 1985; Steenkamp and Baumgartner 1998). Then, this partially invariant model is compared to the initial reference model in which all parameters are unconstrained (Steinmetz et al. 2009).

Results

Tests of Measurement Invariance

Political Affiliation Groups

Measurement invariance was tested for the 5-construct survey instrument across 2 subgroups based on political affiliation (liberals (n = 390) and conservative (n = 342)). It compared the fit of increasingly constrained models. The first model tested was the configural invariance model, which allowed all factor loadings and intercepts to vary freely across the two political affiliation groups. The fit of this model was acceptable (CFI = .944, TLI = .942, RMSEA = .055), indicating that the 5-factor model was a good fit for both conservative and liberals.

The next model tested was metric invariance, which constrained the factor loadings to be equal across groups. The fit of this model proved to be significantly worse than the configural model (ΔCFI = .001, Δdf = 164, Δchisq = 295.121 and a pr(>chisq) ~ 0). These results suggest that the metric invariance model did not provide an adequate fit to the data and was significantly different from the configural invariance model based on chisq test but fits the data based on CFI test (Svetina, Rutkowski, and Rutkowski 2020). Modification fit indices were utilized for better fitting the model but did not yield significant changes. Since measurement invariance could not be established for the political affiliation group with both tests, the following results should be interpreted with caution. Table 3.2 presents the standardized factor loadings and residual variances of the 5-factor model for each political affiliation group.

Table 3.9: Standardized factor loadings, and residual variances for the 5-factor model by political affiliation group

Standardized factor loadings, and residual variances for the 5-factor model by political affiliation group

Construct	Factor Loading (liberals)	Factor Loading (conservatives)	Residual Variance
Awareness/Familiarity	0.84	0.86	0.06
Concern/Urgency	0.76	0.68	0.08
Perception	0.80	0.83	0.02
Involvement	0.79	0.86	0.02
Intended Behavior	0.78	0.82	0.02

The latent means (intercepts) for each construct were estimated separately for conservatives and liberals. The mean for conservatives was set to zero for each construct, and the latent mean for liberals was estimated relative to this reference group. Table 3.3 presents the estimated latent means between conservatives and liberals for each construct.

Table 3.10: Estimated latent means and standardized mean differences by political affiliation group.

Estimated latent means and standardized mean differences by political affiliation group		
Constructs	Latent Mean (conservatives)	Latent Mean (liberals)
Awareness/Familiarity	0.00	0.15
Concern/Urgency	0.00	-0.34
Perception	0.00	0.28
Involvement	0.00	0.20
Intended Behavior	0.00	-0.17

MeasEqSyntax by default estimates the polychoric correlation matrix as the input to the CFA when used with ordinal data. The polychoric correlation matrix is a correlation matrix that is used in SEM to estimate the correlations among latent variables that are measured using ordinal observed variables. It is estimated using a bivariate normal model that takes into account the underlying continuous distribution that generates the observed ordinal data. The polychoric correlation matrix is a useful tool for analyzing ordinal data in SEM because it provides a more accurate estimate of the true correlations among latent variables than the standard Pearson correlation and help in comparative study (Tinsley and Tinsley 1987; McDonald and Ho 2002). Table 3.4 presents the correlation matrix for each of the political affiliation groups.

Table 3.11: Polychoric correlation matrix of the observed variables against latent variables of each political affiliation group

Polychoric correlation matrix of the observed variables against latent variables of each political affiliation group																			
	AW1	AW2	AW3a	AW3b	AW3c	AW3d	AW3e	AW3f	AW3g	AW3h	AW3i	AW3j	AW3k	AW3l	AW3m	AW3n	AW3o	AW3p	AW3q
Awareness/Familiarity (conservatives)	0.65	0.67	0.72	0.74	0.76	0.79	0.74	0.75	0.76	0.78	0.78	0.76	0.72	0.76	0.76	0.75	0.72	0.69	0.76
Awareness/Familiarity (liberals)	0.75	0.71	0.81	0.82	0.82	0.83	0.82	0.81	0.83	0.82	0.85	0.80	0.76	0.84	0.81	0.74	0.76	0.74	0.78
Diff	**-0.10**	**-0.04**	**-0.08**	**-0.09**	**-0.07**	**-0.04**	**-0.07**	**-0.06**	**-0.06**	**-0.04**	**-0.06**	**-0.04**	**-0.04**	**-0.08**	**-0.05**	**0.01**	**-0.04**	**-0.05**	**-0.03**
	CU1a	CU1b	CU1c	CU1d	CU1e	CU1f	CU1g	CU1h	CU1i	CU1j	CU1k	CU1l	CU1m	CU2a	CU2b	CU2c	CU2d	CU2e	CU2f
Concern/Urgency (conservatives)	0.15	0.28	0.13	0.15	0.23	0.36	0.34	0.32	0.36	0.31	0.32	0.25	0.32	0.29	0.24	0.29	0.28	0.25	0.29
Concern/Urgency (liberals)	-0.07	0.13	0.03	-0.02	0.21	0.29	0.22	0.19	0.09	0.07	0.08	0.17	0.13	-0.06	0.03	-0.04	0.01	0.10	0.03
Diff	**0.21**	**0.15**	**0.10**	**0.17**	**0.02**	**0.07**	**0.12**	**0.14**	**0.27**	**0.24**	**0.24**	**0.08**	**0.19**	**0.35**	**0.21**	**0.33**	**0.26**	**0.15**	**0.26**
	CU2g	CU3a	CU3b	CU3c	CU3d	CU3e	CU3f	CU3g	CU4a	CU4b	CU4c	CU4d	CU4e	CU4f	CU4g				
Concern/Urgency (conservatives)	0.27	0.23	0.14	0.22	0.22	0.19	0.27	0.17	0.13	0.15	0.17	0.15	0.20	0.24	0.12				
Concern/Urgency (liberals)	0.02	0.00	0.06	0.01	0.07	0.07	0.06	0.05	0.02	0.02	-0.02	0.08	0.12	0.04	0.08				
Diff	**0.24**	**0.22**	**0.09**	**0.22**	**0.15**	**0.11**	**0.21**	**0.13**	**0.11**	**0.13**	**0.18**	**0.07**	**0.07**	**0.21**	**0.04**				
	IB_E1a	IB_E1b	IB_E1c	IB_E1d	IB_E1e	IB_E1f	IB_E1g	IB_E2	IB_E3a	IB_E3b	IB_E3c	IB_E3d	IB_E3e	IB_E3f	IB_E3g				
Intended Behavior (conservatives)	0.38	0.37	0.46	0.39	0.39	0.45	0.41	0.44	0.39	0.42	0.42	0.35	0.40	0.39	0.35				
Intended Behavior (liberals)	0.23	0.31	0.28	0.24	0.31	0.23	0.30	0.24	0.32	0.33	0.31	0.27	0.33	0.30	0.31				
Diff	**0.14**	**0.06**	**0.18**	**0.15**	**0.08**	**0.21**	**0.11**	**0.20**	**0.07**	**0.09**	**0.11**	**0.08**	**0.07**	**0.09**	**0.04**				
	I1a	I1b	I1c	I1d	I1e	I1f	I1g												
Involvement (conservatives)	0.44	0.40	0.44	0.40	0.43	0.47	0.42												
Involvement (liberals)	0.41	0.42	0.43	0.43	0.45	0.45	0.47												
Diff	**0.03**	**-0.02**	**0.01**	**-0.03**	**-0.02**	**0.02**	**-0.05**												
	P1a	P1b	P1c	P1d	P1e	P1f	P1g												
Perception (conservatives)	0.32	0.35	0.36	0.40	0.35	0.34	0.33												
Perception (liberals)	0.44	0.42	0.45	0.41	0.36	0.37	0.34												
Diff	**-0.12**	**-0.07**	**-0.09**	**-0.02**	**-0.01**	**-0.03**	**0.00**												

The covariance matrix was also evaluated between the groups to the degree to which the latent variables vary together. Table 3.5 presents the covariance matrix of each political affiliation group.

Table 3.12: Covariance matrix (top: conservative and bottom: liberals)

	Awareness/ Familiarity	**Concern/ Urgency**	**Perception**	**Involvement**	**Intended Behavior**
Awareness/ Familiarity	1				
Concern/ Urgency	0.426	1			
Perception	0.494	0.486	1		
Involvement	0.588	0.523	0.647	1	
Intended Behavior	0.572	0.656	0.681	0.783	1

	Awareness/ Familiarity	**Concern/ Urgency**	**Perception**	**Involvement**	**Intended Behavior**
Awareness/ Familiarity	1				
Concern/ Urgency	0.114	1			
Perception	0.532	0.157	1		
Involvement	0.567	0.244	0.596	1	
Intended Behavior	0.387	0.557	0.4	0.555	1

As shown in Table 3.4, there were significant differences in correlation matrix between conservatives and liberals for all 5 constructs. For awareness/familiarity construct, the differences ranged from -.10 to 0.01, indicating that liberals scored higher than conservatives. For concern/urgency construct, the differences ranged from 0.02 to 0.27 which indicated conservatives are more concerned than liberals. Similarly, for intended behavior construct, the difference ranged from 0.04 to 0.21 indicating conservatives more likely to develop behavior regarding sustainability than liberals. For involvement construct, the differences ranged from -.05 to 0.03 both conservatives and liberals are involved in taking actions and finally for perception construct, the differences range from 0 to -0.12 indicating liberals are perceive the issue more than conservatives.

Income Groups

As described in the methodology section, the measurement invariance of the 5-construct survey instrument was examined across two subgroups based on income level (low income (n = 460) and high income (n = 476)). It compared the fit of models with increasing constraints. The first model evaluated was the configural invariance model, which allowed all factor loadings and intercepts to vary freely across the two income levels. The model fit was satisfactory (CFI =.939, TLI =.938, RMSEA =.056), showing that the 5-factor model was a good fit for both low- and high-income levels.

Metric invariance, which limited factor loadings to be equal across groups, was the next model evaluated. This model's fit was not significantly worse to that of the configural model (ΔCFI <.001, Δdf = 164, Δchisq = 180.542, and pr(>chisq) = 0.1786), indicating that factor loadings were consistent across groups. Then, scalar invariance was examined, which required factor loadings and intercepts to be equivalent across groups. This model's fit was not considerably worse than that of the metric model (ΔCFI <.001, Δdf = 77, Δchisq = 76.085, and pr(>chisq) = 0.51), indicating that the intercepts were identical across groups (Svetina, Rutkowski, and Rutkowski 2020). Table 3.6 presents the standardized factor loadings and residual variances of the five-factor model for each income level group.

Table 3.13: Standardized factor loadings and residual variances for the 5-factor model by income level group

Standardized factor loadings and residual variances for the 5-factor model by income level group

Construct	Factor Loading (low income)	Factor Loading (high income)	Residual Variance
Awareness/Familiarity	0.88	0.86	0.03
Concern/Urgency	0.72	0.74	0.02
Perception	0.85	0.83	0.04
Involvement	0.87	0.85	0.03
Intended Behavior	0.84	0.84	0.02

Low income and high-income groups' latent means (intercepts) for each component were estimated separately. The low-income group's mean was set to zero for each construct, and the high-income group's latent mean was estimated relative to this reference group. The estimated latent means between low income and high income for each construct are presented in Table 3.7.

Table 3.14: Estimated latent means and standardized mean differences by income level group.

Estimated latent means and standardized mean differences by income level group		
Constructs	Latent Mean (low income)	Latent Mean (high Income)
Awareness/Familiarity	0.00	-0.17
Concern/Urgency	0.00	0.13
Perception	0.00	-0.09
Involvement	0.00	-0.20
Intended Behavior	0.00	-0.11

Similar to political affiliation group, polychoric correlation matrix which is a default output of using measEqSyntax with ordinal data, is used to compare between the income level groups as it provides a more accurate estimate of the true correlations among latent variables than the standard Pearson correlation and help in comparative study (Tinsley and Tinsley 1987; McDonald and Ho 2002). Table 3.8 presents the correlation matrix for each of the income level group.

Table 3.15: Polychoric correlation matrix of the observed variables against latent variables of each income level group

Polychoric correlation matrix of the observed variables against latent variables of each income level group																			
	AW1	AW2	AW3a	AW3b	AW3c	AW3d	AW3e	AW3f	AW3g	AW3h	AW3i	AW3j	AW3k	AW3l	AW3m	AW3n	AW3o	AW3p	AW3q
Awareness/Familiarity (low income)	0.711	0.683	0.783	0.783	0.796	0.81	0.798	0.802	0.812	0.799	0.824	0.778	0.733	0.797	0.794	0.76	0.753	0.701	0.777
Awareness/Familiarity (high income)	0.685	0.682	0.734	0.768	0.767	0.796	0.735	0.739	0.769	0.795	0.79	0.759	0.73	0.786	0.774	0.721	0.727	0.709	0.757
Diff	**0.03**	**0.00**	**0.05**	**0.02**	**0.03**	**0.01**	**0.06**	**0.06**	**0.04**	**0.00**	**0.03**	**0.02**	**0.00**	**0.01**	**0.02**	**0.04**	**0.03**	**-0.01**	**0.02**
	CU1a	CU1b	CU1c	CU1d	CU1e	CU1f	CU1g	CU1h	CU1i	CU1j	CU1k	CU1l	CU1m	CU2a	CU2b	CU2c	CU2d	CU2e	CU2f
Concern/Urgency (low income)	-0.002	0.213	0.059	0.08	0.134	0.259	0.203	0.165	0.154	0.144	0.174	0.198	0.173	0.035	0.059	2E-04	0.094	0.17	0.131
Concern/Urgency (high income)	0.157	0.205	0.169	0.098	0.314	0.383	0.364	0.369	0.322	0.249	0.229	0.269	0.333	0.244	0.226	0.27	0.25	0.205	0.183
Diff	**-0.16**	**0.01**	**-0.11**	**-0.02**	**-0.18**	**-0.12**	**-0.16**	**-0.20**	**-0.17**	**-0.10**	**-0.05**	**-0.07**	**-0.16**	**-0.21**	**-0.17**	**-0.27**	**-0.16**	**-0.04**	**-0.05**
	CU2g	CU3a	CU3b	CU3c	CU3d	CU3e	CU3f	CU3g	CU4a	CU4b	CU4c	CU4d	CU4e	CU4f	CU4g				
Concern/Urgency (low income)	0.102	0.049	0.051	0.063	0.147	0.11	0.141	0.082	-0.02	0.04	0.031	0.114	0.137	0.109	0.097				
Concern/Urgency (high income)	0.219	0.24	0.204	0.185	0.182	0.175	0.21	0.167	0.229	0.163	0.194	0.178	0.234	0.209	0.149				
Diff	**-0.12**	**-0.19**	**-0.15**	**-0.12**	**-0.03**	**-0.07**	**-0.07**	**-0.08**	**-0.25**	**-0.12**	**-0.16**	**-0.06**	**-0.10**	**-0.10**	**-0.05**				
	IB_E1a	IB_E1b	IB_E1c	IB_E1d	IB_E1e	IB_E1f	IB_E1g	IB_E2	IB_E3a	IB_E3b	IB_E3c	IB_E3d	IB_E3e	IB_E3f	IB_E3g				
Intended Behavior (low income)	0.261	0.29	0.315	0.268	0.353	0.306	0.324	0.322	0.312	0.333	0.318	0.273	0.346	0.305	0.31				
Intended Behavior (high income)	0.388	0.421	0.433	0.398	0.392	0.421	0.404	0.336	0.378	0.414	0.365	0.344	0.374	0.362	0.358				
Diff	**-0.13**	**-0.13**	**-0.12**	**-0.13**	**-0.04**	**-0.12**	**-0.08**	**-0.01**	**-0.07**	**-0.08**	**-0.05**	**-0.07**	**-0.03**	**-0.06**	**-0.05**				
	I1a	I1b	I1c	I1d	I1e	I1f	I1g												
Involvement (low income)	0.406	0.39	0.418	0.415	0.442	0.457	0.416												
Involvement (high income)	0.43	0.421	0.451	0.413	0.435	0.481	0.458												
Diff	**-0.02**	**-0.03**	**-0.03**	**0.00**	**0.01**	**-0.02**	**-0.04**												
	P1a	P1b	P1c	P1d	P1e	P1f	P1g												
Perception (low income)	0.306	0.306	0.325	0.356	0.298	0.31	0.265												
Perception (high income)	0.404	0.424	0.44	0.425	0.381	0.403	0.385												
Diff	**-0.10**	**-0.12**	**-0.11**	**-0.07**	**-0.08**	**-0.09**	**-0.12**												

The covariance matrix was also evaluated between the groups to understand the degree to which the latent variables vary together. Table 3.9 presents the covariance matrix of each income level group.

Table 3.16: Covariance matrix (top: low income and bottom: high income)

	Awareness /Familiarity	**Concern/ Urgency**	**Perception**	**Involvement**	**Intended Behavior**
Awareness /Familiarity	1				
Concern /Urgency	0.177	1			
Perception	0.415	0.244	1		
Involvement	0.549	0.308	0.539	1	
Intended Behavior	0.415	0.531	0.431	0.638	1
	Awareness /Familiarity	**Concern/ Urgency**	**Perception**	**Involvement**	**Intended Behavior**
Awareness /Familiarity	1				
Concern /Urgency	0.376	1			
Perception	0.578	0.386	1		
Involvement	0.603	0.421	0.626	1	
Intended Behavior	0.538	0.66	0.585	0.709	1

As shown in Table 3.8, significant differences were identified in correlation matrix between low income and high income for all constructs except awareness/familiarity. For awareness/familiarity construct, the differences ranged from -.01 to 0.06, suggesting that both low income and high-income population are aware and familiar with the concept of sustainability and SDGs. For concern/urgency construct, the differences ranged from -0.21 to 0.01 which indicated high income are more concerned than low-income population. Similarly, for intended behavior construct, it shows a similar pattern with the difference ranging from -0.01 to 0.13 indicating high income more likely to develop behavior regarding sustainability than low income. For involvement construct, though there is not many differences (-.04 to 0.0) high income still score higher than low income and finally for perception construct, the differences range from -0.07 to -0.12 indicating again high income are perceive the issue more than low income population.

Gender Groups

In a manner, like the two previous groups, the measurement invariance of a 5-construct survey instrument across two subgroups based on gender, specifically male (n=379) and female (n=552) was examined. The fit of models was compared with increasing constraints to evaluate the consistency of the instrument across gender groups.

First, the configural invariance model was assessed, which allowed all factor loadings and intercepts to vary freely across the two gender groups. The model fit was satisfactory (CFI=.94, TLI=.938, RMSEA=.056), indicating that the five-factor model was a good fit for both male and female groups.

Next, the metric invariance model was tested, which constrained factor loadings to be equal across gender groups. The fit of this model was not significantly worse than the configural model (ΔCFI <.001, Δdf = 164, Δchisq = 192.53, and pr(>chisq) = 0.0632), suggesting that the factor loadings were invariant across gender groups. Next scalar invariance was examined, which constrained both factor loadings and intercepts to be equal across groups. However, the fit of this model was significantly worse than the metric model (ΔCFI <.001, Δdf = 77, Δchisq = 100.73, and pr(>chisq) = 0.03615) based on chisq test, indicating that the intercepts were not invariant across gender groups (Svetina, Rutkowski, and Rutkowski 2020). Modification indices were evaluated, and the model was adjusted based on higher modification indices, repeatedly until a satisfactory model was achieved, also known as partial invariance. In this case, partial invariance was achieved by freeing one item each from the concern/urgency construct and the intended behavior construct. Table 3.10 presents the standardized factor loadings, intercepts, and residual variances of the 5-factor model for each gender group.

Table 3.17: Standardized factor loadings and residual variances for the five-factor model by gender group

Standardized factor loadings and residual variances for the five-factor model by gender group

Construct	Factor Loading (male)	Factor Loading (female)	Residual Variance
Awareness/Familiarity	0.87	0.88	0.02
Concern/Urgency	0.72	0.74	0.04
Perception	0.85	0.84	0.02
Involvement	0.87	0.86	0.02
Intended Behavior	0.84	0.83	0.01

Similar approach was implemented as the other two group comparisons to compare the latent means (intercepts) of each component between male and female groups. They are estimated separately for each group. Specifically, the mean for each construct was set to zero for the male group, and the female group's latent mean was estimated in relation to this reference group. The estimated latent means for each construct between male and female groups are shown in Table 3.11.

Table 3.18: Estimated latent means and standardized mean differences by gender group.

Estimated latent means and standardized mean differences by gender group

Constructs	Latent Mean (male)	Latent Mean (female)

Awareness/Familiarity	0.00	0.08
Concern/Urgency	0.00	-0.05
Perception	0.00	0.18
Involvement	0.00	0.12
Intended Behavior	0.00	0.04

Once more, the polychoric correlation matrix was utilized, which is the default output generated by using measEqSyntax with ordinal data, to compare the gender groups. This type of correlation matrix offers a more precise estimate of the true correlations among latent variables than the standard Pearson correlation, making it useful for comparative analysis (Tinsley and Tinsley 1987; McDonald and Ho 2002). Table 3.12 displays the correlation matrix for each of the gender groups.

Table 3.19: Polychoric correlation matrix of the observed variables against latent variables of each gender group

Polychoric correlation matrix of the observed variables against latent variables of each gender group																			
	AW1	AW2	AW3a	AW3b	AW3c	AW3d	AW3e	AW3f	AW3g	AW3h	AW3i	AW3j	AW3k	AW3l	AW3m	AW3n	AW3o	AW3p	AW3q
Awareness/Familiarity (male)	0.712	0.695	0.752	0.757	0.772	0.783	0.745	0.748	0.783	0.783	0.799	0.749	0.723	0.772	0.77	0.73	0.722	0.68	0.772
Awareness/Familiarity (female)	0.694	0.681	0.771	0.792	0.793	0.819	0.785	0.789	0.797	0.807	0.814	0.785	0.739	0.805	0.795	0.751	0.756	0.721	0.767
Diff	**0.02**	**0.01**	**-0.02**	**-0.04**	**-0.02**	**-0.04**	**-0.04**	**-0.04**	**-0.01**	**-0.02**	**-0.01**	**-0.04**	**-0.02**	**-0.03**	**-0.02**	**-0.02**	**-0.03**	**-0.04**	**0.00**
	CU1a	CU1b	CU1c	CU1d	CU1e	CU1f	CU1g	CU1h	CU1i	CU1j	CU1k	CU1l	CU1m	CU2a	CU2b	CU2c	CU2d	CU2e	CU2f
Concern/Urgency (male)	0.085	0.239	0.113	0.056	0.183	0.332	0.289	0.306	0.29	0.181	0.222	0.23	0.246	0.235	0.197	0.224	0.205	0.199	0.189
Concern/Urgency (female)	0.05	0.185	0.1	0.093	0.241	0.298	0.276	0.232	0.2	0.196	0.173	0.224	0.255	0.062	0.095	0.067	0.141	0.169	0.124
Diff	**0.03**	**0.05**	**0.01**	**-0.04**	**-0.06**	**0.03**	**0.01**	**0.07**	**0.09**	**-0.01**	**0.05**	**0.01**	**-0.01**	**0.17**	**0.10**	**0.16**	**0.06**	**0.03**	**0.07**
	CU2g	CU3a	CU3b	CU3c	CU3d	CU3e	CU3f	CU3g	CU4a	CU4b	CU4c	CU4d	CU4e	CU4f	CU4g				
Concern/Urgency (male)	0.18	0.226	0.154	0.172	0.187	0.144	0.142	0.156	0.196	0.195	0.192	0.167	0.204	0.211	0.16				
Concern/Urgency (female)	0.137	0.067	0.095	0.082	0.128	0.126	0.186	0.09	0.02	0.021	0.041	0.107	0.161	0.113	0.08				
Diff	**0.04**	**0.16**	**0.06**	**0.09**	**0.06**	**0.02**	**-0.04**	**0.07**	**0.18**	**0.17**	**0.15**	**0.06**	**0.04**	**0.10**	**0.08**				
	IB_E1a	IB_E1b	IB_E1c	IB_E1d	IB_E1e	IB_E1f	IB_E1g	IB_E2	IB_E3a	IB_E3b	IB_E3c	IB_E3d	IB_E3e	IB_E3f	IB_E3g				
Intended Behavior (male)	0.417	0.408	0.45	0.379	0.428	0.405	0.436	0.431	0.384	0.386	0.363	0.337	0.412	0.33	0.367				
Intended Behavior (female)	0.254	0.315	0.32	0.292	0.331	0.323	0.296	0.277	0.321	0.366	0.324	0.286	0.321	0.332	0.302				
Diff	**0.16**	**0.09**	**0.13**	**0.09**	**0.10**	**0.08**	**0.14**	**0.15**	**0.06**	**0.02**	**0.04**	**0.05**	**0.09**	**0.00**	**0.07**				
	I1a	I1b	I1c	I1d	I1e	I1f	I1g												
Involvement (male)	0.432	0.398	0.443	0.403	0.431	0.472	0.453												
Involvement (female)	0.417	0.416	0.432	0.43	0.449	0.47	0.432												
Diff	**0.02**	**-0.02**	**0.01**	**-0.03**	**-0.02**	**0.00**	**0.02**												
	P1a	P1b	P1c	P1d	P1e	P1f	P1g												
Perception (male)	0.38	0.352	0.398	0.417	0.358	0.322	0.346												
Perception (female)	0.348	0.378	0.378	0.371	0.33	0.383	0.318												
Diff	**0.03**	**-0.03**	**0.02**	**0.05**	**0.03**	**-0.06**	**0.03**												

The covariance matrix was also examined between the groups to assess the extent to which the latent variables vary in tandem. Table 3.13 displays the covariance matrix for each gender group.

Table 3.20: Covariance matrix (top: male and bottom: female)

	Awareness /Familiarity	**Concern /Urgency**	**Perception**	**Involvement**	**Intended Behavior**
Awareness /Familiarity	1				
Concern /Urgency	0.33	1			
Perception	0.507	0.398	1		
Involvement	0.582	0.446	0.596	1	
Intended Behavior	0.547	0.669	0.578	0.699	1
	Awareness /Familiarity	**Concern /Urgency**	**Perception**	**Involvement**	**Intended Behavior**
Awareness /Familiarity	1				
Concern /Urgency	0.222	1			
Perception	0.49	0.248	1		
Involvement	0.578	0.287	0.573	1	
Intended Behavior	0.424	0.536	0.455	0.654	1

As shown in Table 3.12, there is not significant differences in correlation matrix between male and female for three of the five constructs - awareness/familiarity construct, involvement construct, and finally perception construct. Whereas for concern/urgency construct, the differences ranged from -0.04 to 0.18 where males scored higher than females which indicated males are more concerned than females and for intended behavior construct, the difference ranged from 0.0 to 0.16 where again males score higher than female indicating males more likely to develop behavior regarding sustainability than females.

SEM model

Table 3.1 shows the demographic statistics of the sample collected for the model. The sample size was 936, with male (n=379) and female (n=552) participants. The mean age of the participants was 43 years (SD = 12.69). Table 3.14 describes the descriptive statistics of the sample population collected who answered questions in the Likert scale of 1-5.

Table 3.21: Descriptive Statistics for the Six Constructs

Constructs	Mean	SD	Skewness	Kurtosis
Awareness/Familiarity	2.922	1.32	0.08514	-1.2126
Concern/Urgency	2.17	1.11	0.77478	-0.1497
Involvement	2.887	1.24	0.07814	-1.0191
Perception	2.866	1.14	0.06149	-0.8201
Intended Behavior	2.635	1.28	0.37823	-0.9184
Behavior	1.991	0.87	0.81507	0.78526

The hypothesized structural equation model was tested using the lavaan package in R with ordinal data. The model fit was evaluated using the chi-square test, the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA).

The chi-square test was significant, indicating poor model fit ($\chi 2$ = 13631.621, df = 3466, $p < .001$). However, given that the chi-square test is highly sensitive to sample size, we also evaluated the model fit using the CFI, TLI, and RMSEA. The CFI and TLI values were .937 and .935, respectively, indicating good model fit. The RMSEA value was .056, indicating acceptable model fit.

The standardized path coefficients and their associated p-values are presented in Figure 5.2.

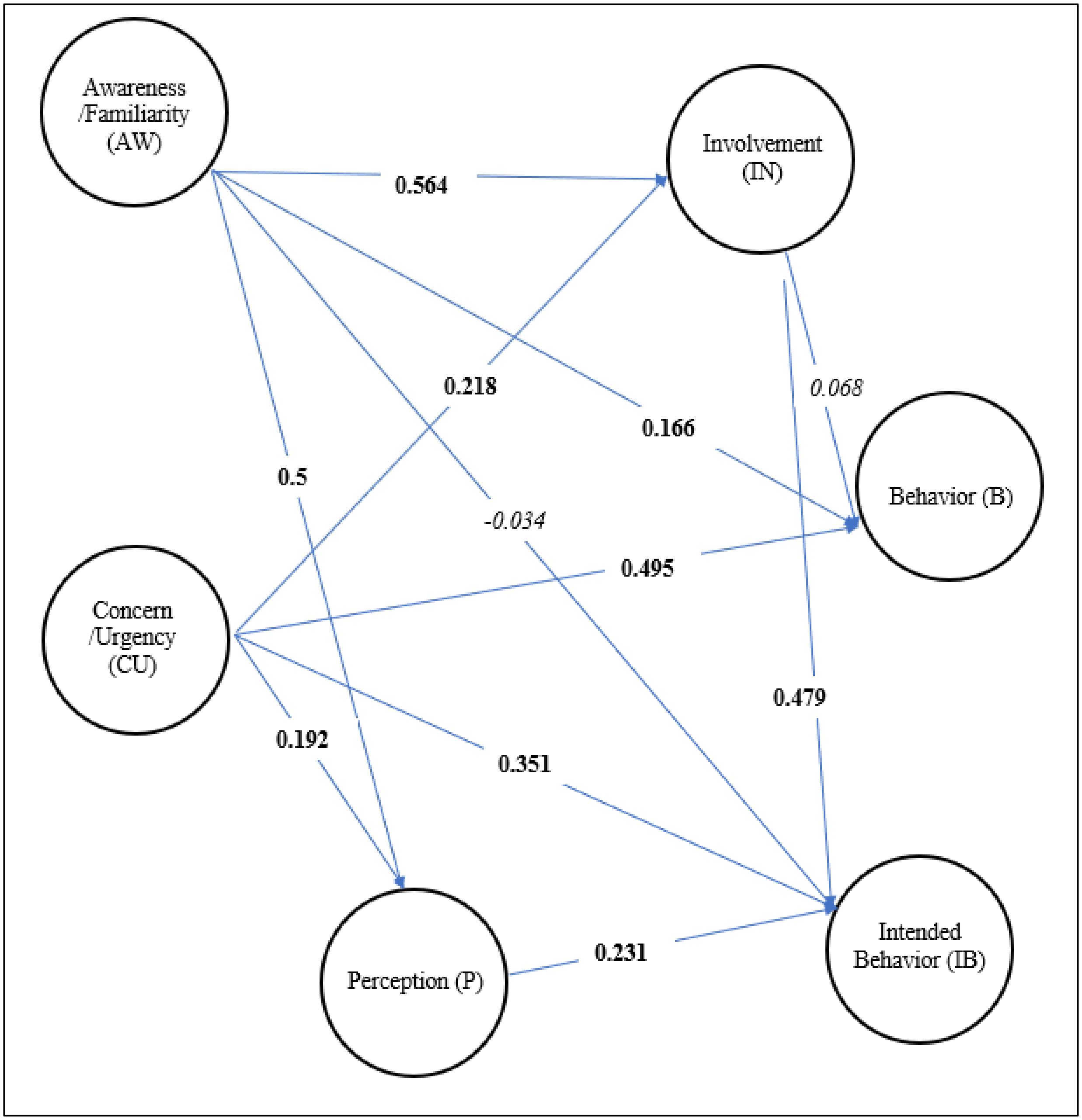

Figure 3.6: Standardized Path Coefficients for the SEM

Table 3.15 shows the regression and covariance output of the SEM model. The model explained 36.8% of the variance in intended behavior and 64.1% of the variance in behavior. All path coefficients were statistically significant ($p < .05$) except for the path from awareness/familiarity to intended behavior and the path from involvement to behavior.

Table 3.22: Regression and covariance output of SEM

Regressions						
Constructs	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
involvement ~						
Concern/Urgency	0.305	0.036	8.422	0	0.218	0.218
Awareness/Familiarity	0.635	0.027	23.185	0	0.564	0.564
perception ~						
Concern/Urgency	0.262	0.041	6.39	0	0.192	0.192
Awareness/Familiarity	0.549	0.03	18.587	0	0.5	0.5
behavior ~						
involvement	0.048	0.03	1.609	0.108	0.068	0.068
Awareness/Familiarity	0.133	0.032	4.107	0	0.166	0.166
Concern/Urgency	0.491	0.044	11.265	0	0.495	0.495
Intended Behavior ~						
Concern/Urgency	0.472	0.034	13.705	0	0.351	0.351
perception	0.228	0.031	7.34	0	0.231	0.231
involvement	0.461	0.03	15.354	0	0.479	0.479
Awareness/Familiarity	-0.037	0.042	-0.885	0.376	-0.034	-0.034

Covariances:						
	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.AW1 ~~						
.AW2	0.305	0.016	18.488	0	0.305	0.696
.IB_E1a ~~						
.IB_E1b	0.186	0.014	12.926	0	0.186	0.61

.CU3g ~~						
.CU4g	0.29	0.021	14.094	0	0.29	0.544
.CU1l ~~						
.CU1m	0.277	0.02	13.545	0	0.277	0.54
.AW3e ~~						
.AW3f	0.147	0.011	13.899	0	0.147	0.581
.CU2a ~~						
.CU2b	0.252	0.02	12.535	0	0.252	0.578
Awareness/Familarity ~~						
Concern/Urgency	0.121	0.014	8.761	0	0.262	0.262
.intended Behavior ~~						
.behavior	0.061	0.009	6.618	0	0.252	0.252

The results of the structural equation model show that concern/urgency had a significant positive effect on involvement ($\beta = .218$ $p < .001$) and perception ($\beta = .192$, $p < .001$), supporting the hypothesis that higher levels of concern/urgency lead to greater involvement and perception. Similarly, awareness/familiarity had a significant positive effect on involvement ($\beta = .564$ $p < .001$) and perception ($\beta = .5$, $p < .001$), indicating that greater awareness/familiarity also lead to greater involvement and perception showing a stronger relationship than concern/urgency.

In terms of the path from involvement, awareness/familiarity, and concern/urgency to behavior, all paths were significant except the path from involvement to behavior. Concern/Urgency had the strongest effect on behavior ($\beta = .495$, $p < .001$), followed by awareness/familiarity ($\beta = .166$, $p < .001$). This suggests that higher levels of concern/urgency, and awareness/familiarity are associated with greater levels of behavior whereas the relationship between involvement and behavior could not be established which partially proves hypothesis 3.

Finally, the path from concern/urgency, perception, involvement, and awareness/familiarity to intended behavior was also significant, with three constructs having a significant positive effect on intended behavior and awareness/familiarity significance could not be established. Involvement had the strongest effect on intended behavior ($\beta = .479$, $p < .001$), followed by concern/urgency ($\beta = .351$, $p < .001$) and perception ($\beta = .231$, $p < .001$). Though the significance of awareness/familiarity could not be established it showed a small negative effect on intended behavior as $\beta = -0.034$ and $p = .376$ partially proving the hypothesis 4.

Direct and indirect effects of constructs on intended behavior and behavior was established by adding se=”bootstrap”, test="scaled.shifted", estimator="DWLS", verbose=TRUE code to the SEM model. Table 3.16 presents the direct and total effects of the constructs on intended behavior and behavior. The direct effect is the effect of each construct on the outcome variable, while the total effect is the sum of the direct and indirect effects of each construct. The indirect effect is the effect of each construct on the outcome variable that is mediated by the other constructs in the model.

Table 3.23: Direct and Total Effects of the Constructs on Intended Behavior and Behavior

Constructs	Indirect Effect on Intended Behavior	Indirect Effect on Behavior	Total Effect on Intended Behavior	Total Effect on Behavior
Awareness/Familiarity	0.418	0.031	0.381	0.164
Concern/Urgency	0.2	0.015	0.673	0.506

******the indirect effect on intended behavior and behavior includes involvement and perception predicted through awareness/familiarity; and concern/urgency as they also predicts involvement and perception.*

The results indicate that all 5 constructs are important predictors of intended behavior and behavior. As shown in Table 3.15 and 3.16, involvement was the strongest predictor of intended behavior, concern/urgency was the strongest predictor of behavior, while concern/urgency overall have greater total effect on intended behavior and behavior whereas awareness/familiarity has greater indirect effect on the two constructs.

Discussion

Measurement Invariance

This study aimed to test the measurement invariance of a 5-constructs survey instrument across two subgroups based on political affiliation (liberals and conservatives), income level (low income and high income), and gender (male and female). The study compares the fit of different models with increasing constraints to evaluate the consistency of the instrument across the subgroups with groups. Additionally, the polychoric correlation matrix was used to estimate the correlations among latent variables that were measured using ordinal observed variables.

The results for measurement invariance showed that the configural invariance model, which allowed all factor loadings and intercepts to vary freely across both groups, had an acceptable fit for political affiliation groups, income level groups, and gender groups. The results also showed that the metric model, which constrained the factor loadings to be equal across the groups, had a good fit for the 5-factor model for both income level and gender groups. However, it had a significantly worse fit than the configural invariance model for the political affiliation groups indicating that measurement invariance could not be established. The lack of measurement invariance means that the differences between the liberals and conservatives for each construct should be interpreted with caution. The scalar model, which required factor loadings and intercepts to be equivalent across groups, was not evaluated for political affiliation groups, but provided a good fit for income level groups, and had to be modified for partial invariance for gender groups.

After establishing measurement invariance to some degree in each of the three groups, polychoric correlation matrices were evaluated to understand the difference among the sub-groups of each political affiliation, income level, and gender groups, respectively. The results showed that there were major differences between the two political affiliation groups' polychoric correlation matrices suggesting that the factor structure may not be the same for both political affiliation groups. The results of this study on political affiliation groups have implications for researchers using survey instruments to compare groups based on political affiliation. The lack of measurement invariance suggests that the survey instrument may not be measuring the same constructs in the same way for both political affiliation groups. As a result, researchers should exercise caution when interpreting and comparing the results of survey instruments across political affiliation groups. Future research should explore the reasons for the lack of measurement invariance and consider using alternative measurement models or instruments that are more invariant across political affiliation groups.

For income level groups, the findings suggest that the survey instrument had measurement invariance across the two income groups, indicating that the scores were comparable. The results also showed that though low income group and higher income groups' awareness about and current involvement in sustainability policies were comparable, high-income individuals had higher level of environmental concern and perception and more likelihood to develop behavior towards sustainable practices than among low-income individuals, which could have implications for environmental policies and programs aimed at promoting environmental awareness and sustainability proving the hypothesis.

Finally, for the two subgroups based on gender, male and female, the fit of the scalar invariance model was significantly worse than the metric model. This indicates that the intercepts were not invariant across gender groups. The authors then adjusted the model based on higher modification indices until a satisfactory model was achieved, also known as partial invariance. In this case, partial invariance was achieved by freeing one item each from the concern/urgency construct and the intended behavior construct, suggesting that caution should be exercised when interpreting differences in mean scores between the groups. The results suggested that there are not significant differences in correlation matrix between male and female for three of the five constructs - awareness/familiarity construct, involvement construct, and finally perception construct. Whereas for concern/urgency construct and intended behavior construct, males scored higher than females which indicated males are more concerned and more likely to develop behavior regarding sustainability than females which contradicts previous studies and the hypothesis of this study to some extent. This can have huge implications on creating outreach activities surrounding sustainability policies and practices targeting certain genders.

SEM Model

The results of the study support the hypothesis that concern/urgency, awareness/familiarity led to greater involvement and perception, which in turn lead to heightened behavior and intended behavior. The findings are consistent with previous research on the role of emotions and attitudes in predicting behavior (Ajzen 1991).

The results also highlight the importance of concern/urgency as a predictor of behavior and involvement as a predictor of intended behavior. Involvement is defined as the degree to which a person is personally relevant to the issue or problem being studied (Zaichkowsky 1985). The study's results indicate that heightened levels of involvement correlate with greater levels of intended behavior. Therefore, stakeholders should prioritize emphasizing the urgency of the matter, as this can lead to changes in behavior. Additionally, they should encourage individuals who are already involved to become more engaged in sustainability issues in which they are not currently involved, thereby promoting participation.

Limitation of the Study

There are several limitations to this study. One limitation of the study is that the sample was drawn from a specific population and may not be representative of other populations. The study sample was composed of SEUS residents mostly from urban areas, which may limit the generalizability of the findings. Another limitation of the study is that the data collected were self-reported, which can introduce response bias. Respondents may have answered questions in a socially desirable manner, or they may not have accurately represented their true beliefs, attitudes, or behaviors. Additionally, the study used a cross-sectional design, which means that causality cannot be inferred. The study did not examine how the constructs change over time or how they are affected by other variables. Furthermore, the study only examined the measurement invariance of the 5-construct survey instrument across gender, political affiliation, and income groups. It did not consider other potential demographic or cultural differences that may exist due to limitations in the number of responses among other subgroups. Finally, the study relied on a single survey instrument, the SS, to measure the constructs of interest, which may not fully capture the complexity of these constructs. Other measures or methods may provide a more nuanced understanding of the constructs under study.

Conclusion

In conclusion, the study aimed to test the measurement invariance of a 5-construct survey instrument across subgroups based on political affiliation, income level, and gender. The results showed that the survey instrument had acceptable fit across all subgroups in terms of configural invariance, gender, and income level subgroups for metric invariance, and only income subgroup for scalar invariance. The lack of measurement invariance for political affiliation groups suggests that the survey instrument may not be measuring the same constructs in the same way for both groups, indicating that caution should be exercised when interpreting and comparing the results across political affiliation groups. The study also highlighted that high-income individuals had higher levels of environmental concern and perception and were more likely to develop behavior towards sustainable practices than low-income individuals. Moreover, males scored higher than females on concern/urgency and intended behavior constructs, which may have implications for creating outreach activities surrounding sustainability policies and practices targeting certain genders which contradicts the hypothesis providing other insights. This might be the result of constraining the study to SEUS citizens which can be different from the population studied in other studies. The findings also supported the hypothesis that concern/urgency and awareness/familiarity lead to greater involvement and perception, which in turn lead to greater behavior and intended behavior. The findings have implications for the design of persuasive messages and interventions aimed at promoting behavior change. Specifically, the results suggest that messages and interventions should aim to increase awareness/familiarity, heighten concern/urgency, and increase involvement and perception in order to promote behavior change. Further research is needed to confirm and extend these findings, should explore the reasons for the lack of measurement invariance and consider alternative measurement models or instruments that are more invariant across subgroups.

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CHAPTER 4: CONNECTING URBAN EXPANSION WITH SUSTAINABILITY: MAPPING AND PREDICTING LAND COVER CHANGES OF SMALL AND MEDIUM SIZE CITIES IN ALABAMA USING MACHINE LEARNING TECHNIQUES

Introduction

These results from chapter 3 show the importance of understanding diverse aspects of community engagement especially in SEUS for attaining sustainable future for all. Cities have proven to be the breeding ground for activation, innovation, and change through community engagement (Bernard 2019). Therefore, understanding evolving city landscape with exponentially increasing urban population is very crucial in the pursuit of a sustainable future. It is also worth noting that most of the urban research is carried out on large, global cities such as Atlanta, New York, Tokyo, Kolkata, and Dhaka, amongst others (Yang 2002; Islam and Ahmed 2011). Because of this, there is a scarcity of research on SMSC, which frequently sees unprecedented population expansion even though they are inadequate to manage it. In the United States alone, between 1982 and 1997, there was an increase of 34% in the total quantity of land that was used for urban and built-up purposes (Ralph J., Jeffrey D., and Mark 2004). With the rising trend in urbanization, there was a significant jump of 13% urban population change between the year 1980 to 2020 as reported by the US Census (Bureau 2022b). There will likely be a continuation of urban growth over the course of the next 25 years, according to statistical forecasts; however, the extent of this development will differ between regions (Ralph J., Jeffrey D., and Mark 2004). The United States Census Bureau has assigned a population-based ranking of each city in the United States. According to this ranking, cities with a number lower than 101 is regarded big cities, between 101 and 200 are regarded to be medium-sized and higher than 200 as small cities (Bureau 2022a). The population range for medium size city ranges from 98,000 to

210,000 residents in 2010. In Alabama (the study area state), a southern state in the United States, there is only one large city (Birmingham, which ranks 100) and three medium-sized cities (Montgomery: rank 105, Mobile: rank 120, and Huntsville: rank 126), according to these numbers and the ranking methodology. The remaining ones are classified as small-sized cities and are ranked higher than position 200. Research has also shown that medium-sized cities have a faster population growth rate than a select few of the larger cities (such as Detroit, Cleveland, Pittsburg, Saint Louis, and New Orleans), which all lost more than 20 % of their population during the 1990s (Forman and Vey 2002). Additionally, in another study, the southern and western states of the United States showed to have medium-sized cities with the highest rates of population growth (Bureau 2020), one of which is Alabama. The findings of above research point to a possible migratory pattern in which residents of numerous large cities move to a greater number of SMSC.

The SEUS, in particular, is also highly vulnerable to the effects of climate change, such as sea-level rise and excessive heat. Temperatures in the Southeast are projected to rise by 2.2 °C during the next century, accompanied by a rise in the frequency and severity of droughts (KC et. al 2021; KC et. al. 2015), providing a need to study these states further. Therefore, this study focuses on SMSC in Alabama (Table 4.1) for Land Use Land Cover (LUCC) and impacts of the frequency of hazardous weather events, their surging population, and the presence of large populations of communities of color and those living in poverty (Burkett et al. 2001).

Table 4.24: Growth (increase and decrease) in population for the ten cities in Alabama from 1980 to 2020. Source: United States Census Bureau, 2020 (Bureau 2022c).

Study Areas (Based on city population)	**Population**		**Population Change, 1990 to 2020**	
	1990	**2020**	**Number**	**Percent (%)**

Birmingham	265968	197575	-68393	-25.71
Montgomery	187106	198665	11559	6.18
Mobile	196278	184952	-11326	-5.77
Huntsville	159789	216963	57174	35.78
Tuscaloosa	77759	100618	22859	29.40
Hoover	39788	92589	52801	132.71
Dothan	53589	71175	17586	32.82
Decatur	48761	57804	9043	18.55
Auburn	33830	78564	44734	132.23
Madison	14904	58357	43453	291.55

There are few studies conducted in the cities of Alabama related to LUCC which includes integrating land use change with transportation model for Montgomery (Clay 2010), studying LUCC in Mobile Bay (J. T. Ellis et al. 2011), studying urban heat island and environmental effects for Huntsville (Lo, Quattrochi, and Luvall 1997; Rahman, Mitra, and Marzen 2013), studying the relationship between LUCC and temperature in Auburn/Opelika (Hug et al. 2013), improving LUCC classification for Huntsville (Tadesse, Coleman, and Tsegaye 2011), and exploring effects of LUCC on air quality for central Alabama (Superczynski and Christopher 2011). However, none of these studies explore in-depth multiple decadal LUCC of the top 10 SMSC of Alabama and using those to predict their “business-as-usual” future LUCC. This is important to understand as SMSC in SEUS are particularly vulnerable to extreme events due to their exponentially growing population which includes large vulnerable populations of communities of color and those living in poverty (Burkett et al. 2001) to promote a sustainable and resilient community.

Studying past and present trends combined with predicting future land use change is an important aspect of urban research. The UN has forecasted that 68.4% of the population will reside in urban areas by 2050 referred to as city in this context (United Nations 2019). A rise in the city's population places a greater strain on the city's infrastructure and overall quality of life. Because of this, there has been a natural increase in the urban built-up areas (Lambin and Ehrlich 1997) leading to land use changes, which are necessary to support the rising population. It has been decided to utilize the amount of urban built-up as a proxy measure to indicate the expanding population. In this context, the term "urban built-up" refers to the geographic region that is bounded within a city by the human built impermeable surfaces. This region can be found described in recent research on remote sensing as impervious surfaces (Yang 2002). Using technical tools such as GIS and remote sensing to determine the expansion of urban centers coupled with land use changes in various parts of the world is becoming increasingly common. The advancement of remote sensing and digital image processing offers unparalleled opportunities for a broader range of locations to detect changes in land cover more accurately, with decreasing prices and processing times (Dewan and Yamaguchi 2009).

This literature review will focus on a few key research studies related to urbanization on a global scale using GIS and remote sensing. The transformation of land cover in Fez, Morocco, one of the most ancient imperial cities, was investigated and studied using satellite images and secondary datasets of thirty years, beginning in 1984 and continuing through 2013 (El Garouani et al. 2017). Another study was conducted in Tamilnadu, a city in Chennai, India. The study was conducted to examine the consequences of increasing population and urban sprawl on productive agricultural areas and pristine forests using images from 1991 to 2016 and were used to project land cover for 2027 (Padmanaban et al. 2017). The change and urbanization expansion in Bas-rah Province, Southern Iraq was also studied using LUCC classification of images of Landsat TM in 1990 and Landsat ETM+ in 2003 (Hadeel, Jabbar, and Chen 2009). In addition, for the purpose of designating LUCC, a supervised classification was carried out for the Northwestern coast of Egypt (Shalaby and Tateishi 2007). The United States has been the site of a significant amount of study into the use of remote sensing to better understand LUCC. Xiaojun Yang (2002) monitored the urban spatial growth in the Atlanta metropolitan region in 2002 using an unsupervised classification method that was based on Landsat TM data between 1973 and 1999 (Yang 2002). Similarly, Yuan et al. (2005) looked at land cover classification and change analysis in the twin cities of Minnesota (Yuan et al. 2005). The cities of Birmingham and Hoover, both located in Alabama, were analyzed by Trousdale (2010) using supervised classification. Over a span of thirty-four years, he analyzed the expansion of suburban sprawl (1974 to 2008). The findings indicate that there was a gradual loss in forests, agricultural lands, and green space over the course of the research period; in addition, there was an in-crease in urban and residential LUCC in the form of built-up in the metropolitan area (Trousdale 2010). With the advancement of technology, cloud-based platforms aiding remote sensing research such as GEE are being introduced (Mutanga and Kumar 2019). GEE is a cloud based geospatial analysis tool that enables users to visualize and study satellite imageries and other derived datasets of our planet. GEE is utilized by scientists and non-profit organizations for remote sensing research, disease outbreak prediction, natural resource management, and more (Lambin and Ehrlich 1997; Dewan and Yamaguchi 2009; El Garouani et. al 2017; Padmanaban et. al 2017). Scientists have used GEE in many land use land cover classification studies as well. Phan et al. (2020) used GEE to examine the effect of various composition approaches and different imageries on classification outcomes (Phan, Kuch, and Lehnert 2020). Similarly, Tassi and Vizzari (2020) developed and tested an object-based classification approach using three techniques: the Simple Non-Iterative Clustering (SNIC) algorithm to detect spatial clusters, the

Gray-Level Co-occurrence Matrix (GLCM) to determine cluster texture indices, and Random Forest (RF) or Support Vector Machine (SVM) for the categorization of the clusters in GEE (Tassi and Vizzari 2020). Becker et al. (2021) used Landsat-8 images in the GEE to automatically classify LUCC in the Sao Francisco Verdadeiro River hydrographic basin, western Paraná state (Becker et al. 2021). Additionally, Liu et al. (2018) created multi-temporal global urban land maps based on Landsat imagery during the 1990–2010 era with a five-year interval ("urban land" in these maps refers to artificial cover and constructions such as pavement, concrete, brick, and stone) utilizing the power of GEE (Liu et al. 2018).

Remote sensing also serves as a tool to implement land use change models. Land use change models serve as analytical aids for determining the causes and effects of land use dynamics. Such data could serve as a foundation for scientific and efficient land-cover planning, management, and ecological restoration, as well as a guide for regional socioeconomic growth. Using land use classified maps from the past, it is feasible to construct a model to forecast trends in land cover changes over a specific time period. There are a variety of land use models available, each originating from a distinct academic discipline (Verburg et al. 2004). They can be categorized as analytical equation-based models (Palacios Orejuela and Toulkeridis 2020), statistical models (Tayyebi, Perry, and Tayyebi 2014), evolutionary models (Termansen, McClean, and Preston 2006), cellular models (Hamad, Balzter, and Kolo 2018), Markov models (Wang, Munkhnasan, and Lee 2021), hybrid models (Munthali et al. 2020), expert system models (Giuliani et al. 2022) and multi-agent models (Ralha et al. 2013). Currently, the most prominent models for monitoring and predicting land use change are cellular, agent-based, and mixed models (Liping, Yujun, and Saeed 2018). The CA-Markov model combines the Markov model with the Cellular Automata model. This model combines the long-term predictions of the

Markov model with the capability of the Cellular Automata (CA) model to simulate spatial variation in a complex system, and it can simulate LUCC change (Liping, Yujun, and Saeed 2018). Both cellular automata (CA) and the Markov model have significant advantages in the analysis of land use change, as well as limitations. The Markov model for land use changes has been widely applied, although it is difficult to forecast the spatial pattern of land use changes with the classic Markov model. The CA model equipped with powerful spatial computing can be utilized to simulate the spatial variation of the system with precision. A CA–Markov model is a robust method for spatial and temporal dynamic modeling of land use changes because geographic information systems (GIS) and remote sensing (RS) can be incorporated effectively (Sang et al. 2011). The CA–Markov model incorporates the advantages of the time series and spatial predictions of the Markov and CA theories, and it can be utilized to stimulate the Spatial–Temporal Pattern. The CA–Markov model also considers the suitability of land use changes and the impact of ecological, social, and economic factors on land use changes. Numerous research (Islam and Ah-med 2011; Hamad, Balzter, and Kolo 2018; Sang et al. 2011; Babbar et al. 2021; Anand and Oinam 2020; Leta, Demissie, and Tränckner 2021; Mihailescu and Cîmpeanu 2020) have utilized the CA-Markov model to track and predict changes in land use and landscape.

Characteristics of Alabama cities

Population

Based on Table 4.1 there is an exponential increase in population growth in all the cities except for Birmingham and Mobile. All the cities chosen had a population change greater than 5% from 1990 to 2020 (Table 4.1). With the exception of Birmingham and Mobile, the population of most of Alabama's largest cities has increased significantly during the past few decades. On the other hand, the population of Birmingham and Mobile has decreased over the years. The numbers of people living in Madison, Hoover, and Auburn have all grown considerably over the course of the past three decades. Table 4.1 shows that major cities like Birmingham and Mobile are growing slowly (25.71% and 5.77% population were lost, respectively from each city from 1990 to 2020) compared to other cities like Hoover and Madison with more than 130% and 290% growth shown from 1990 to 2020, respectively. Birmingham and Mobile presence in the study aided in determining if population loss affects urban development and growth.

Poverty

Alabama is one of the poorest states in the United State with a median household income of $52,035. According to the U.S Census 2022, Alabama is the second poorest state with a poverty rate of 15.69% (US Census 2022). Cities such as Mobile, Tuscaloosa, Birmingham, and Auburn were included in the study with the percentage of individuals living below the poverty line as 20.7%, 24.0%, 25.9%, and 27.3% respectively fall under the 15 poorest cities in Alabama.

Race

Race composition of Alabama cities vary from city to city. Based on U.S census 2022 and American Community Survey (ACS) the racial composition of Alabama consists of 67.5% of white, 26.59% of African American, 2.44% of two or more races, 1.53% of other race, 1.39% of Asian, 0.51% of native American, and 0.04% of native Hawaiian or pacific islander. The racial composition of the 10 cities selected in this study is shown in Table 4.2 below.

Table 4.25: Racial composition of Alabama Cities. Source: United States Census Bureau, 2022 and ACS.

Cities	White (%)	Black (%)	Two or more	Asian (%)	Other race (%)	Native American (%)	Native Hawaiian (%)

			races (%)				
Birmingham	26.59	68.29	2	1.25	1.63	0.2	0.04
Montgomery	31.46	60.80	2.87	3.25	1.43	0.18	0.01
Mobile	43.56	51.1	2.47	1.75	0.81	0.3	0.02
Huntsville	59.74	31.77	3.02	2.58	2.35	0.41	0.13
Tuscaloosa	50.89	44.10	1.47	2.48	0.77	0.28	0.02
Hoover	71.59	18.46	2.77	5.31	1.75	0.1	0.03
Dothan	60.3	34.75	2.42	1.36	0.91	0.26	0.00
Decatur	66.47	22.32	3.7	0.26	3.7	0.19	0.05
Auburn	71.03	17.60	1.73	8.76	0.77	0.1	0.00
Madison	76.03	13.90	3.31	5.59	0.77	0.38	0.03

Employment

Alabama's unemployment rate slightly differs from the United States being 2.6 compared to 3.6 in August 2022 according to Alabama Department of Labor (Bureau of Labor Statistics 2022). Unbalanced growth of employment is one of the main reasons for unbalanced urban growth. Table 4.3 shows the unemployment rate of Alabama cities in August 2022. The unemployment rate of the cities ranges from 1.9 to 4.4% of the population in the 10 cities leading to different patterns of growth.

Table 4.26: Unemployment Rate of Alabama Cities. Source: Alabama Department of Labor, 2022 and ACS

Cities	Unemployment Rate (%)
Birmingham	3.9
Montgomery	3.8
Mobile	4.4
Huntsville	2.6
Tuscaloosa	3.4

Hoover	1.9
Dothan	3.0
Decatur	2.5
Auburn	2.9
Madison	2.0

Housing

According to the US census Alabama consists of total of 2313642 housing units as of July 1, 2021, out of which 69.2% are owner-occupied housing units for 2016-2020 (US Census 2022). In the year 2021, 2100 new building permits were granted in all of Alabama (Zillow data 2023). Stacker compiled a list of cities with the fastest growing home prices in Alabama using data from Zillow (Zillow data 2023). Below is Table 4.4 showing how the housing prices have changed for cities in 2023.

Table 4.27: Housing price change of Alabama Cities. Source: Zillow data, 2023

Cities	1 year housing price change Rate (%)
Birmingham	+12.9 to +20.6
Montgomery	+18.1
Mobile	+19.4
Huntsville	+21.7 to +34.5
Tuscaloosa	+20.4
Hoover	+12.9 to +20.6
Dothan	NA
Decatur	+21.1
Auburn	+26.5
Madison	+21.7

Transportation

In Alabama, most of the commute is done with cars. Some of the cities do provide limited public transportation networks but are mostly low-density car-dependent neighborhoods. Table 4.5 shows the cities and the public transportation network name available in those cities.

Table 4.28: Public transportation network of Alabama Cities. Source: APTAAdmin. 2023

Cities	**Public Transportation Network Name**
Birmingham	TRANSIT AGENCIES
	MAX (Birmingham Jefferson County Transit Authority, BJCTA, Metro Area Express)
	CLASTRAN (Central Alabama's Specialized Transportation, Birmingham Regional Paratransit Consortium)
	OTHER SITES
	BRTAA (Birmingham Regional Transportation Alternatives Analysis)
	BJCTAC (Birmingham-Jefferson County Transit Advisory Committee)
	CTC (Citizens for Transit Coalition)
Montgomery	TRANSIT AGENCIES
	MATS (Montgomery Area Transit System; Montgomery Area Paratransit System, MAPS)
	OTHER SITES
	MTC (Montgomery Transportation Coalition)
Mobile	MBF (Mobile Bay Ferry)
Huntsville	Huntsville Public Transportation
	TRAM (Transportation for Rural Areas of Madison County)
Tuscaloosa	Tuscaloosa Transit Authority
Hoover	TRANSIT AGENCIES
	MAX (Birmingham Jefferson County Transit Authority, BJCTA, Metro Area Express)
	CLASTRAN (Central Alabama's Specialized Transportation, Birmingham Regional Paratransit Consortium)
	OTHER SITES
	BRTAA (Birmingham Regional Transportation Alternatives Analysis)

	BJCTAC (Birmingham-Jefferson County Transit Advisory Committee) CTC (Citizens for Transit Coalition)
Dothan	WTA (Wiregrass Transit Authority)
Decatur	NARCOG Regional Transit Agency
Auburn	LETA (Lee County Transit Agency, Lee-Russell Council of Governments) Tiger Transit (Auburn University)
Madison	Huntsville Public Transportation TRAM (Transportation for Rural Areas of Madison County)

Urban models, Urban form, and Urban forces

The spatial structure of the cities is driven by economic and social forces (deBlij 1993). There are three fundamental urban structure models (Figure 4.1).

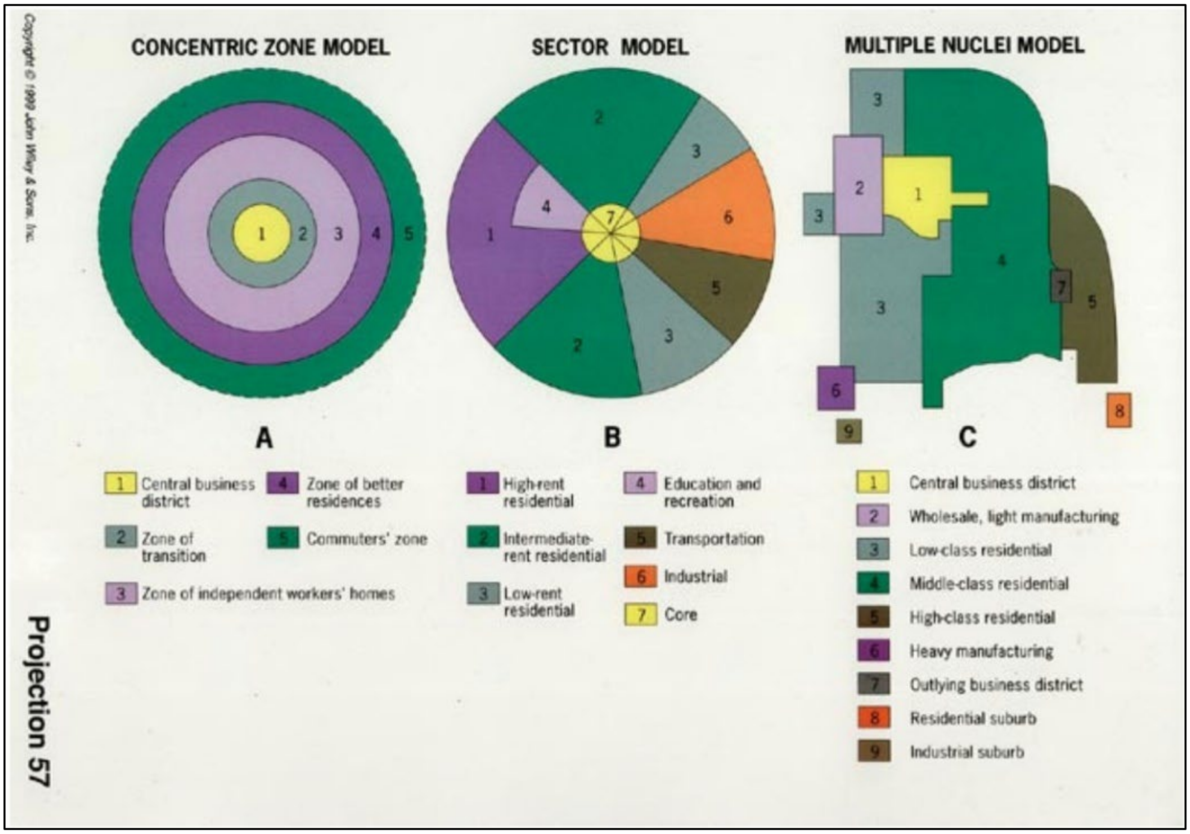


Figure 4.7: Models of urban structure. Adapted from John Wiley and Sons (1999)

(1) Concentric zone model (Figure 4.1(a))

The Concentric zone model, also known as CCD model, was created by sociologist named Ernest Burgess in 1925 (Burgess 2008). It was proposed based on the observations of Chicago to explain the distribution of social groups within urban areas. It consists of five concentric zones depicting different urban land usage in concentric rings. The five zones are:

1. the Central Business District (CBD) (region 1), containing shops, offices, banks, government buildings, and hotels.
2. the transitional area, a zone of residential deterioration, also marked by the encroachment of business and light manufacturing.
3. the zone of workingmen's homes, a ring of closely built but adequate residences of the urban blue-collar labor force.

4. the next zone (region 4) consists of middle-class residences, and out-central-city/inner suburban areas, characterized by greater affluence and spaciousness.
5. the commuters' zone where residents commute to the CBD to work.

(2) Sector model (Figure 4.1(b))

The sector model, also known as Hoyt model, was proposed by land economist Homer Hoyt in 1939 (Adams 2005). It is modification of CCD model to account for the influence of major transportation routes. In contrast to CCD model, it explains the growth of cities along transportation routes without it being in concentric rings.

(3) Multiple nuclei model (Figure 4.1(c))

Harris and Ullman (1945) established the multiple nuclei model, which divides cities into functional zones. The model depicts how cities can grow around numerous functions. Harris and Ullman (1945) still saw the CBD as the main center of trade, but they expected specialized cells of activity would arise based on activity requirements, rent-paying abilities, and the tendency for economic activity to cluster. Transportation corridors have light manufacturing and retail. Heavy industry would be on the city's border, surrounded by lower-income people, and commuter suburbs and smaller service centers would comprise the metropolitan perimeter (Harris and Ullman 1945).

These different urban models can show varied spatial patterns of growth due to influential factors like presence of transportation routes and water bodies which has been established in past studies (Mubea, Ngigi, and Mundia 2011; Guan et al. 2020; Araya and Cabral 2010). Two basic forces that rule the development of an urban area's functions, shape, and pattern are centrifugal and centripetal (Colby 1933). The former may clarify how functions and populations move from the center to the periphery of a city, while the latter keeps those functions in the center and makes it the gravitational center for the entire urbanized area (Colby 1933). Several urban functions and forces have resulted in different urban types (linear, grid, radial, etc.) (Furundzic and Furundvzić 2013). A linear pattern runs parallel to a major urban transit route (interstate, high-way, or railway) or physical infrastructure (such as a river) (Furundzic and Fu-rundvzić 2013). The grid pattern is the product of transportation routes being accessible and functions being available in areas that grow from restricted locations such as river or road junctions or islands (Rodrigue 2013). Centrifugal forces along many transportation routes primarily create the radial pattern (Rodrigue 2013). Most of the expansions of urban areas follow the lines of major transportation routes. As a result, sometimes, spatial pattern of growth was linear and sometimes radial or grid.

Urban models explain how the urban areas are structured whereas urban forms and forces explain how spatial growth pattern of an area. The model, form, and function together explain how a city will grow which is used as a basis to analyze the growth of cities studied in this chapter.

Drivers of land use change

Land use policies also often determine land conversion. To create realistic models of land use changes one needs to identify drivers of changes (Veldcamp and Lambin 2001). Traditionally, the focus for drivers is on biophysical attributes (e.g., altitude of terrain, slope, or soil type) but land use change is also human induced. Hence land use change models need to incorporate data on a wide range of socioeconomic drivers. Lack of spatially explicit data and technical limitations in combining social and biophysical data hinder the incorporation of social, political, and economic issues. Biophysical data are often derived from raster-formatted satellite data. Censuses and surveys are used to collect socioeconomic data. Biophysical data observation units are cells (pixels), but socioeconomic data use artificial enumeration districts (ED) or sampling locations. Socioeconomic data must be disaggregated into modeling-based cells to match people with pixels. There is another related issue as well. One needs to find the best possible way to relate driver variables that cannot be measured directly into the model (e.g., Distance to a road or town). Two aspects of land use change drivers are important for land use modeling. One is selecting drivers (explanatory variables); the other is quantifying land use and driving force interactions. The considerations are taken into account when selecting the driver variables. There is one limitation though. The socio-economic data was not considered for this study as 10 cities needed to be analyzed.

Land use model validation methods

Model validation compares the behavior of a model with a system. A model is valid if it describes the modeled system accurately and provides answers to its intended queries (Casti 1997). Predictive models predict the future states of a given real system; explanatory models explain significant concepts or processes; and heuristic models invent and reveal previously unknown aspects of a system through learning.

The model is compared to reality using subjective and objective testing. Modeling and analytical objectives dictate the validation strategy. Occasionally, the objective of urban land use modeling is to explain or forecast macro trends utilized in general planning. Sometimes, the emphasis is placed on the micro-level location of a particular urban zone.

Comparing expected and actual maps validates land use models. Remote sensing and GIS applications' geographical linking and zooming capabilities aid visual comparison. It's impossible to visually compare every pixel due to their number. This is a qualitative approach. Hence objective metrics are required for better comparison. A contingency table which is created by visually inspecting random sites and calculating agreement indices lacks location information. This results in problems calculating accurate error percentage. Therefore, chisquare-based statistics such as phi, and kappa-based statistics such as kappa are popular to conduct such analysis. There are other model validation approaches. Serneels and Lambin (2001) used graph analysis to validate a land-use model. A graph depicts the likelihood of projected change versus pixels converted. Turner et al. (1989) validated spatial simulation models using multiple-resolution fitting. It compares specific cells. The size of a cell spans from one pixel to the entire image. The weighted mean is used to determine fit. This method can accurately replicate location. In another method, Lowell (2001) devised to assess land use change maps is based on areal data. This method involves comparing the area of each land use class in the map to the area of the corresponding land use class in a reference map which is typically a more accurate and up-to-date map. Receiver operating characteristic (ROC) curve, another model validation technique, was recently applied to land use change modeling in order to compare simulated and actual change (Pontius 2000). In the 1950s, ROC curves were developed to decode noisy radio signals. Pontius and Schneider (2001) illustrated how to evaluate a suitability map's depiction of likely development zones using ROC. ROC technique examines the correctness of a model that predicts an event by comparing an appropriate image representing the event's probability to a binary image indicating where that class really occurs. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) for different classification thresholds. The area under the ROC curve (AUC) indicates the overall performance of the model, with values closer to 1 indicating better performance. One advantage of the ROC curve is that it is not affected by the class distribution in the data, unlike other metrics such as accuracy, precision, and recall. This is particularly important in land use models, where the distribution of land use classes can be highly imbalanced. Additionally, the ROC curve allows for the comparison of multiple models and the selection of the best-performing model based on the AUC value. This study uses kappa statistics and ROC to validate the two models – the past and present LUCC model and the future land use change prediction model respectively.

Cities are characterized by a multitude of activities that are carried out over space and time. To better understand the underlying causes of these changes, it is necessary to investigate how the city has evolved over time. By gaining this knowledge, it is possible to anticipate future changes and formulate plans to promote urban sustainability.

Therefore, this study aims to quantify the changing dynamics of urban built-up expansion in Alabama over the past few decades, centering its attention on the 10 cities in Alabama with the highest populations (Table 4.1) using GEE and Terrset Land Change Modeler (LCM) ("TerrSet 2020 Geospatial Monitoring and Modeling Software" 2022). These cities make up the state's top 10 population centers. Although Alabama as a whole is experiencing relatively slow population growth, specific cities within the state are experiencing radically contrasting patterns of urban development. Such exponential changes to population growth within a short span of time can lead to unprecedented increase in impermeable areas leading to various sustainability issues. Therefore, it is extremely important to study the trend of land use changes and make projections on the future expansion of cities, especially Alabama SMSC which has potential to grow more. Additionally, this study utilized CA-Markov model accessed through Terrset LCM to track and predict changes in urban built-up of Alabama's cities. Additionally, the following two research tasks have been carried out to conduct an analysis of the patterns of urbanization in the state of Alabama:

1. Determine the expansion of urban built-up areas over time (1990 to 2020) for the

10 Alabama cities (population change greater than 5% from 1990 to 2020 (Table 4.1)) using a supervised classification technique in GEE (Figure 4.2).

2. Project future urban growth scenarios (2050) for all 10 cities using cellular automata (CA) Markov model combined with GIS based on the LUCCs in 2010 and 2020.

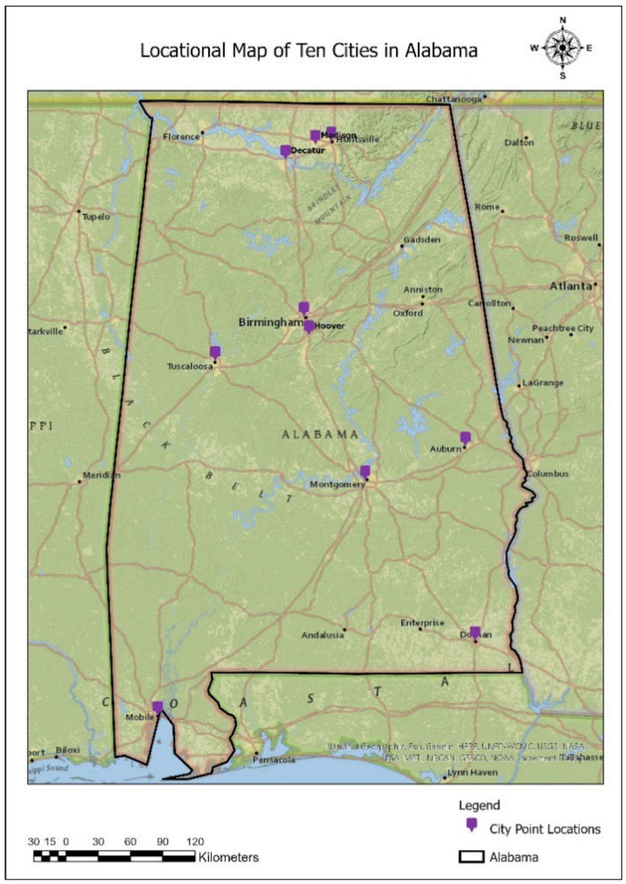


Figure 4.8: Location of 10 cities in Alabama

The following section of the chapter will detail the materials and procedures utilized to develop the models in this chapter, as well as the outcomes of those models.

Methods

Materials and Methods

Urban Built-up Expansion

Data

GEE provides a massive amount of selection for Earth observation data (EOD) encompassing satellite images from popular platforms such as Sentinel, Landsat, and MODIS, as well as other climate and demographic data. In this study, we used atmospherically corrected Landsat 5 and Landsat-8 surface reflectance Tier 1 data for years 1990, 2000, 2010, 2020, and 2021. Area of interest including city boundaries and surrounding rural areas was created in ArcGIS pro and imported into GEE using the shape-file upload option. The unit of analysis was the pixel, with each pixel in Landsat representing 30 m × 30 m. LUCC was divided into four major classes: water bodies, vegetation, barren land, and built-up areas. All green areas were considered vegetation, while rivers and ponds were considered water bodies. The study made use of visible bands – red, green, blue, and other bands such as near-infrared, and short-wave infrared for Landsat 5 and Landsat 8 imageries for the analysis (Table 4.6).

Table 4.29: Landsat 5 and Landsat 8 band information used for the LUCC classification.

Data Layer	**Source**	**Bands Used**	**Wavelength**	**Spatial Resolution (m)**
Landsat-5 Thematic Mapper (TM) surface reflectance Tier 1	Google Earth Engine (GEE), data accessed via the U.S. Geological Survey (USGS)	Blue (Band 1)	0.45-0.52	30
		Green (Band 2)	0.52-0.60	30
		Red (Band 3)	0.63-0.69	30
		Near-Infra-Red (Band 4)	0.77-0.90	30

		Short-Wave Infra-Red 1 (Band 5)	1.55-1.75	30
Landsat-8 Operational Land Imager surface reflectance Tier 1	Google Earth Engine (GEE), data accessed via the U.S. Geological Survey (USGS)	Blue (Band 2)	0.45-0.51	30
		Green (Band 3)	0.53-0.59	30
		Red (Band 4)	0.64-0.67	30
		Near-Infra-Red (Band 5)	0.85-0.88	30
		Short-Wave Infra-Red 1 (Band 6)	1.57-1.65	30

Methods

In order to classify the images into desired land use land cover classification the methodology shown in Figure 4.3 was used. The images were imported using 'ee.ImageCollection' function and the areas of interest created in ArcGIS pro was imported into the script using the 'ee.featurecollection' function. The images were filtered for dates from January 1 to December 31 for each year, no cloud and no cloud shadows. A composite image was then created with the filtered input images using the median function which resulted in a median value assigned to each pixel in the whole image stack, resulting in a single image for the entire image collection. The normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), modified normalized difference water index (MNDWI), and bare soil index (BSI) were calculated and added to the composite image as bands for improved classification. NDVI and NDBI were added to better differentiate between natural and built-up areas. BSI is traditionally used to differentiate bare areas such as houses, roads, bare open spaces, and eroded areas. It can prove beneficial to classify built-up areas (Wentzel 2002; Zha, Gao, and Ni 2003). MNDWI is added for better classification of urban and water features as it can effectively suppress or remove built-up land noises and vegetation and soil noises (Xu 2006). It is necessary to classify water efficiently as they are used later to calculate distance from anthropogenic changes and distance from water for future LUCC predictions.

The NDVI (Pettorelli et al. 2005) is the normalized difference between the NIR and red bands, the NDBI (McFEETERS 1996) is the normalized difference between the NIR and SWIR bands, the MNDWI (Singh et al. 2015) is the normalized difference between GREEN and SWIR bands, and the BSI (Rasul et al. 2018) is the difference between the combination of RED, SWIR, BLUE and NIR bands as shown in equations (1), (2), and (4):

$$NDVI=NIR-RED/NIR+RED \tag{1}$$

$$NDBI=NIR-SWIR/NIR+SWIR \tag{2}$$

$$MNDWI = GREEN - SWIR/GREEEN+SWIR \tag{3}$$

$$BSI = ((RED+SWIR) - (NIR+BLUE)) / ((RED+SWIR) + (NIR+BLUE)) \tag{4}$$

The composite image was also used to create training samples for each type of land use class: water, vegetation, urban, and barren. In total 5,038 polygons for all 10 cities for each year analyzed were created for training and loaded into GEE as feature collection. The training samples were created as polygons using visual interpretation in GEE. 100 polygons for each land use type for each city were created. The edge pixels were avoided to provide the algorithm with polygons containing pixel values belonging to each landuse type for best results. Since NDVI, NDBI, and MNDWI were added as bands in the composite image the other bands were also normalized. 60% of the training samples were randomly selected for classification and 40% for validation. The composite image was then classified using RandomForest (RF) algorithm available within GEE into the desired classes. There are other algorithms such as classification and regression tree (CART), support vector machine (SVM) available with GEE for LUCC. RF is the most commonly used classifier that builds an ensemble classifier (Loukika, Keesara, and Sridhar 2021) by combining many CART trees. Multiple decision trees are generated by RF utilizing a random selection of training datasets and variables (Loukika, Keesara, and Sridhar 2021). RF is constructed by using a technique called bagging in which individual decision trees serve as parallel estimators (Yıldırım 2021). Because of this increasing the number of trees in R, it does not cause overfitting. After a certain point, adding more trees does not improve the accuracy of the model, but it does not detract from the accuracy either (C. Ellis 2022). For this analysis the number of decision trees used was 50. The classified images were then clipped for de-sired AOI and exported as .tif files to google drive to be imported into ArcGIS pro and TerrSet LCM for further analysis.

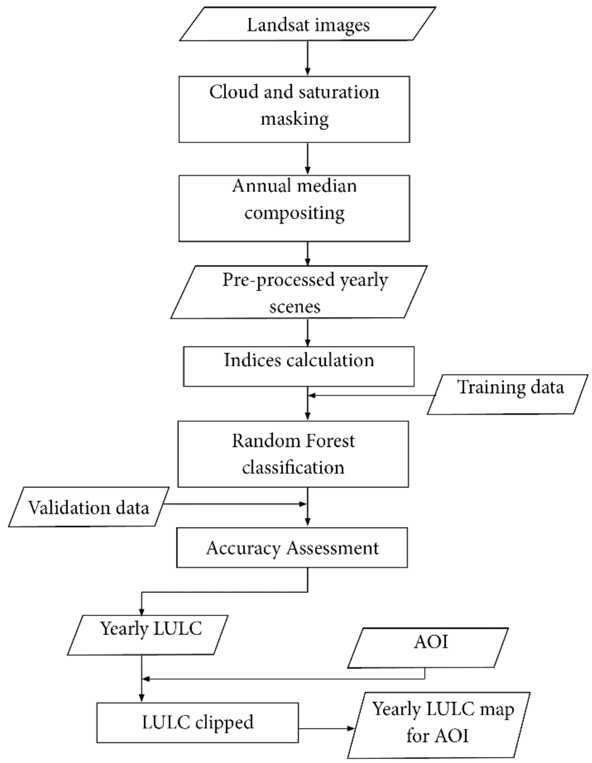


Figure 4.9: Flowchart showing this study's LUCC classification in GEE

Accuracy Assessment

To understand the results of the classification, an accuracy assessment is required. It is vital that the thematic classification is accurate because important application decisions will be made using these data. The polygons were created using satellite imagery of 30 m spatial resolution and visual interpretation and were divided into training and validation sets. 60 %, or 3022 polygons, were used for training and 30 %, or 2015 polygons, were used as testing sets for all 10 cities. GEE includes a confusion matrix method that validates and then evaluates the classification accuracy of the images. The following equations are used to compute the overall accuracy (OA) and kappa coefficient (k):

$$OA = (V_c/V_t) \times 100 \quad (5)$$

where V_c is the number of pixels classified correctly and V_t is the total number of pixels.

$$k = \frac{N \sum_{i=1}^{n} m_{ii} - \sum_{i=1}^{n}(C_i G_i)}{N^2 - \sum_{i=1}^{n}(C_i G_i)} \quad (6)$$

where i = class number, N = total number of classified values compared to true values, mii = number of values belonging to the truth class i that have also been classified as class i (i.e., values found along the diagonal of the confusion matrix), Ci = the total number of predicted values belonging to class i, and Gi = the total number of truth values belonging to class i. For each class, the consumer accuracy is derived by the percentage of correctly categorized pixels to the total number of classified pixels. Producer accuracy is also measured by the ratio of correctly classified pixels to total pixels in the reference data for each class. Classification errors are compared to errors in completely random classes to estimate the proportionate reduction in errors. The magnitude is often in the range of -1 to +1. If the value is more than +0.5 (Loukika, Keesara, and Sridhar 2021), the classification is considered acceptable.

Future Urban Growth

Future growth predictions for urban areas are essential for understanding and mitigating the effects of rising human activities in cities. The future growth of all 10 urban areas has been predicted using IDRISI TerrSet LCM software for 2050 based on the results from the supervised classification conducted in GEE for the year 2010. The workflow of the process used for the prediction of land use change into the future is shown in Figure 4.4. According to Clark Labs, LCM is an integrated and innovative land planning and decision-making tool that is fully functional in the TerrSet software. LCM has an automated, user-friendly flow that simplifies the complexities of change analysis and rapidly analyzes LUCC change patterns, predicts the change, and validate the predicted outputs as well.

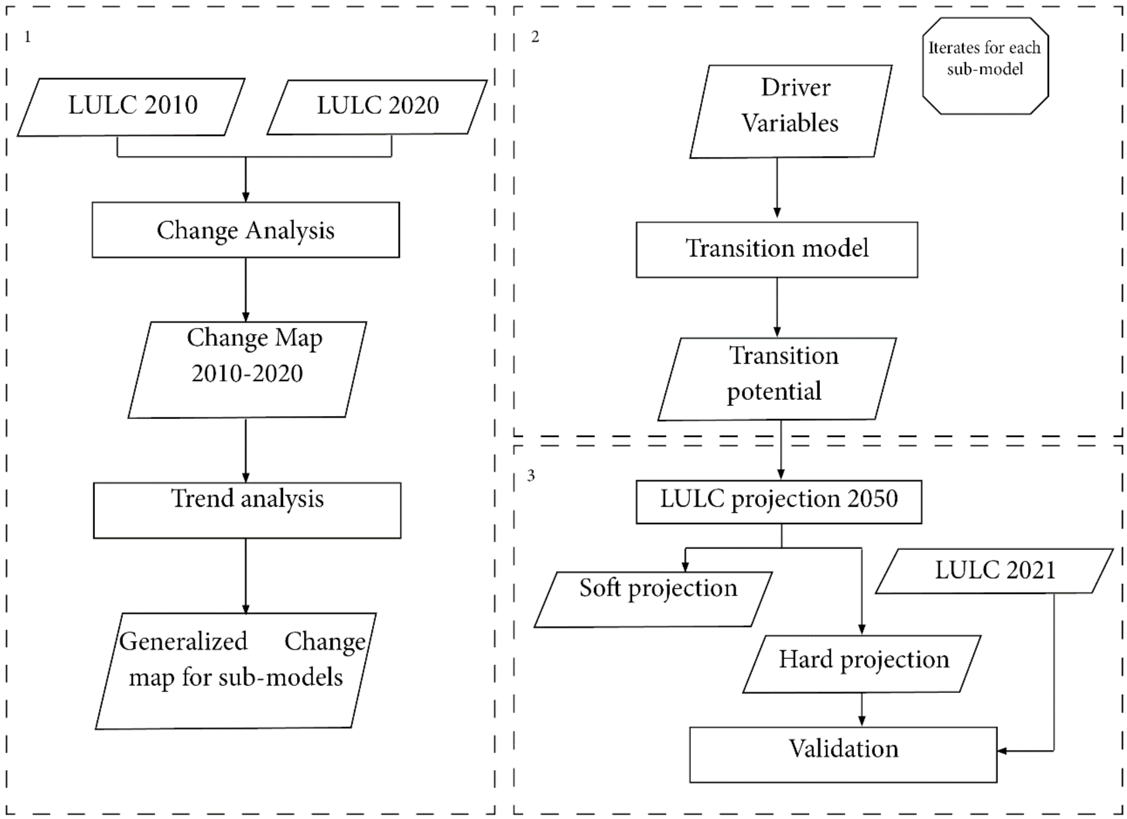


Figure 4.10: Flow diagram showing this study's Change detection model.

Change Analysis

Change is evaluated between time 1 and time 2 (2010 and 2020 in this study) between two land cover maps. It is done as transitions from one land cover state to another by evaluation of gains and losses, net change, persistence, and specific transitions both in maps and graphical format. This is done to identify dominant transition that can be grouped and modeled, also known as sub-models in the transition potential step. Each of these sub-models are modeled separately and at the end each of those sub-models are combined with all other sub-models for the final prediction. The results of change analysis of different land covers between the years

2010 and 2020 are explained in the results section of this chapter.

Transition Potential

After the change analysis the next step is transition potential modeling where the potential of the land to transition is identified. Transition potential maps are created which are maps of suitability for each transition. They can consist of a single or group of transitions that are believed to have the same underlying driver variables which are used to model the historical change process. A collection of such transition potential maps is created and organized within each transition sub-model identified in change analysis step that has the same underlying driver variables. The underlying driver variables which were used in this study are digital elevation model (DEM), slope, aspect, distance from roads, distance from water bodies, distance from settlements, and evidence likelihood layer. Driver variables used to evaluate these transitions potential map for Mobile is shown in Figure 4.5. The underlying driver variables utilized in LCM can be either static or dynamic and can be recalculated and reentered at regular intervals. The DEM was extracted from USGS Aster 30m resolution DEM. The slope and aspect were calculated and created from the DEM in ArcGIS Pro. For the distance from road, settlement, and waterbody, layers from OpenStreetMap data and datasets provided from the city governments for 2010 were used. The vector layers were changed to raster and combined to create a final layer for road, settlement, and waterbody. These layers were imported into TerrSet and the distance layer was created using the distance function in the software. The evidence likelihood layer is created from change analysis transition of the change analysis step and landcover of 2010. Multi-Layer Perceptron (MLP) neural network, Decision Forest (DF) machine learning, Logistic Regression, Weighted Normalized Likelihood (WNL), Support Vector Machine (SVM), or a similarity-weighted instance-based machine learning tool (SimWeight) are used to model the transition which are later used to predict future scenarios. Multi-Layer Perceptron (MLP) was used for this study to create the transition potential maps. The choice of MLP is based on the assumption that the driver variables for all transitions are the same, can accurately model all of the transitions that are gathered into a sub-model, can model non-linear relationships, and can model multiple transitions simultaneously.

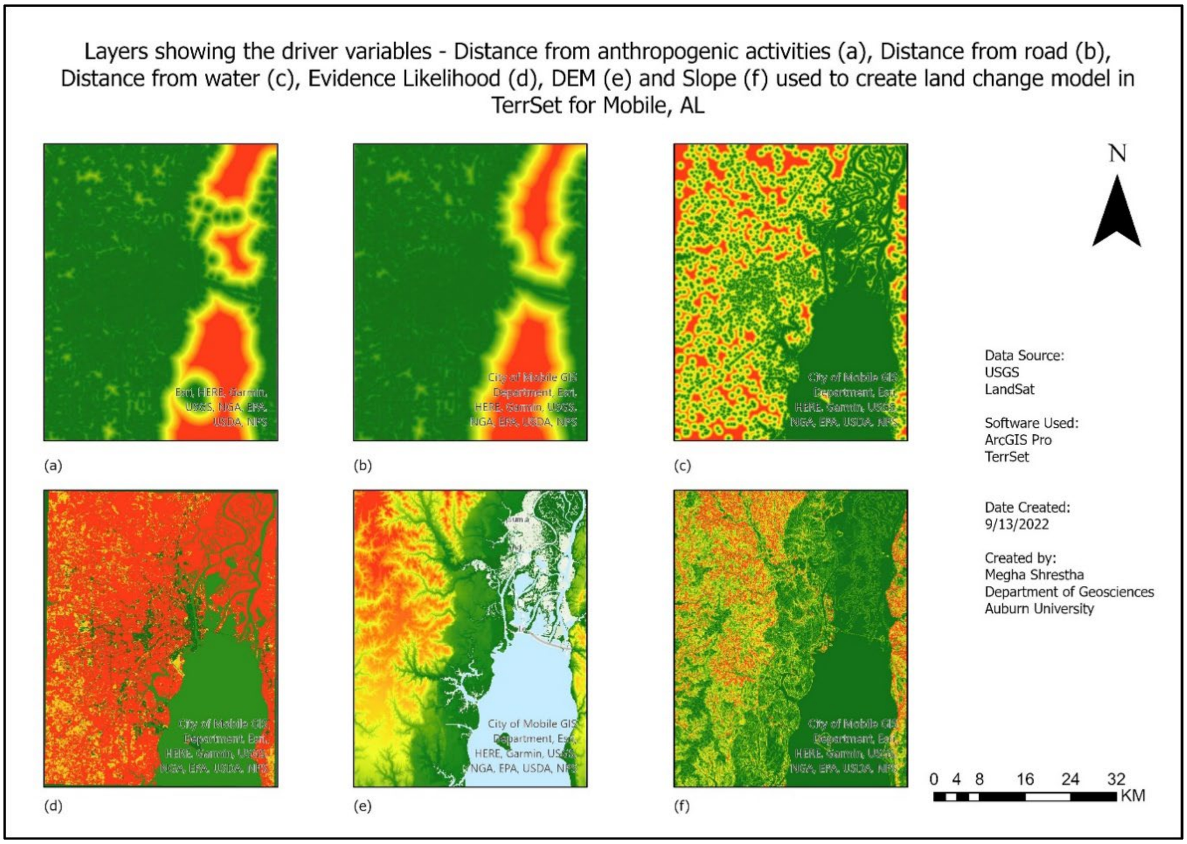


Figure 4.11: Driver variables used for change prediction (Mobile)

Change Prediction

Change prediction is the last stage of future land change study. On the basis of historical change rates from change analysis step and the transition potential model from transition potential step, LCM is able to anticipate a future condition for a suitable future date. Additionally, LCM permits the incorporation of incentives and limits, such as zoning maps and future infrastructure plans. This study estimated the landuse in 2050 using CA Markov, preserving three variables (distance from roads, distance from water bodies, and distance from settlements) as dynamic, and DEM, slope, and evidence likelihood as static. This research did not include any restrictions or incentives. LCM generates two types of predictions: (1) hard predictions and (2) soft predictions. Based on a multi-objective land allocation (MOLA) module (Dzieszko 2014), a hard prediction generates a predicted map (Megahed et al. 2015) where each pixel is allocated one of the land cover classes based on its highest likelihood. Soft prediction assesses the risk that a pixel may transition to another land category by developing a vulnerability map in which each pixel is assigned a value between 0 and 1 (Megahed et al. 2015).

Model Validation

Model validation is a very important step in the modelling process (Adhikari and Southworth 2012). The accuracy of the model can be assessed by validation panel in the change prediction tab of the LCM. It helps to evaluate the quality of the predicted land use map in relation to a map of reality. It is conducted using a 3-way crosstabulation between the later landcover map, the prediction map, and a map of reality and ROC statistics (also known as the Area Under the Receiver Operating Characteristic Curve - or AUC). 2021's simulated map created in change prediction in LCM is compared with 2021's actual LUCC map created with supervised classification in GEE. ROC is used to determine how effectively a continuous surface predicts the locations given a Boolean variable's distribution. It is calculated as a graph between the rate of true positives on the vertical axis and rate of false positives on the horizontal axis. Its value ranges between 0 and 1, where 1 shows a perfect fit and values closer to 0.0 shows a random fit. For this analysis the threshold value for calculating the ROC statistics used was 100 and the soft prediction of landcover for year 2021 was used as input file and the actual change between 2010 and 2021 was used as a reference file. For 3-way crosstabulation the images of hard prediction of 2021 and classified image of 2021 were used as inputs. The output will illustrate the accuracy of the model results with a raster with green, red, and yellow pixels where:

A | B | B = Hits (green) i.e., Model predicted change and it changed

A | A | B = Misses (red) i.e., Model predicted persistence and it still changed

A | B | A = False Alarms (yellow) i.e., Model predicted change and it persisted.

Result

This paper had two parts, one is the LUCC of the 10 most populated cities of Alabama from 1990 to 2021 and second, the future growth prediction of all 10 cities of Alabama up to 2050. To quantify urban expansion and future growth, GIS techniques in GEE and TerrSet LCM were used, respectively.

Land use and Land cover Analysis

Many previous studies proved the efficiency of satellite image and remote sensing classifying LUCC. A supervised classification approach with random forest algorithm in GEE was used to classify the images. Random training samples were collected from each image for the years 1990, 2000, 2010, 2020, and 2021 for each city and used to classify the images. After that, an accuracy assessment was performed to validate the classification of each image.

Figure 4.6 is a graphical representation of urban built-up area expansion from 1990 to 2020 for each city. As depicted, all the cities have been growing throughout the decade. Some of the steepest growth rates can be seen for Auburn, Dothan, Tuscaloosa, and Mobile. All these cities are small cities as compared to medium-sized cities such as Birmingham and Huntsville. The graph also represents a steady growth of cities up to 2010 and a steep increase in urban areas in the last decade.

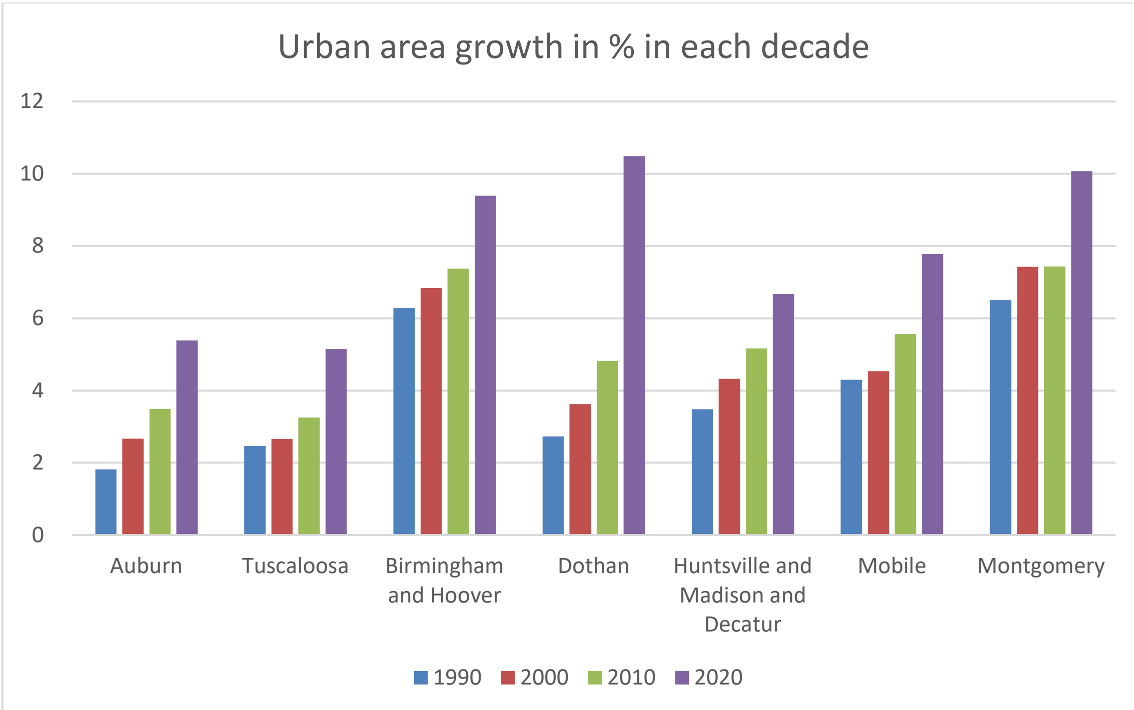


Figure 4.12: Urban Built-up Area Statistics (1990-2020)

As explained above, different urban areas can depict diverse spatial patterns of growth based on functions, shape, and pattern – concentric zone, sector model, multi-nuclei model, and centripetal, centrifugal, linear, grid, and radial patterns. Alabama cities follow such patterns of growth. Birmingham and Dothan having the interstate running through it has a linear growth; Mobile being around gulf shores had grid pattern of urban expansion and cities like Auburn, Montgomery, and Tuscaloosa had a radial pattern due to the growth being around university or water body. Table 4.7 shows the net addition of urban built-up area from 1990-2020 for all 10 cities. It indicates that Dothan, Auburn, and Tuscaloosa have the greatest net addition in urban area study area and Birmingham, and Hoover have the least from 1990 to 2020.

Table 4.30: Net Addition of Urban Built-up from 1990-2020 for 10 Study Areas.

Study Areas	1990	2020	Net addition (%)

	Area(ha)	%	Area(ha)	%	
Auburn	1072	1.82	3174	5.38	196.08
Tuscaloosa	5087	2.46	10630	5.15	108.96
Birmingham and Hoover	19104	6.28	28550	9.39	49.45
Dothan	1785	2.73	6868	10.49	284.76
Huntsville and Madison and Decatur	10362	3.48	19843	6.67	91.50
Mobile	8874	4.30	16058	7.77	80.96
Montgomery	6795	3.29	10518.21	10.07	54.79

This study also reveals more conversions in certain categories. Mostly the non-urban category of LUCC has been encroached by urban built-up area. Below explains the LUCC changes for all 10 SMSC in Alabama.

Birmingham and Hoover

As mentioned earlier, the population of Alabama's largest urban area, Birmingham shrunk by 25.7 percent from 1990 to 2020 while the adjacent Hoover urban area grew by over 132.71 percent (Table 4.1) according to census data. Although urban built-up expansion cannot be inferred using population as a variable, however for both Birmingham and Hoover their urban built-up increased over the same time period. Table 4.7 shows the net addition of built-up area for both Birmingham and Hoover to be 49.45% from 1990 to 2020.

For Birmingham, this addition was mainly concentrated in central parts following interstate 65 (north-east to south-west direction) such as downtown and university areas. Significant growth of Hoover took place from north to south directions. The linear pattern of urban expansion was along interstate 65 (I-65) which also goes from north to south direction. Based on Table 4.7 and Figure 4.7 these cities have added 49.45% of urban areas from 1990 to 2020.

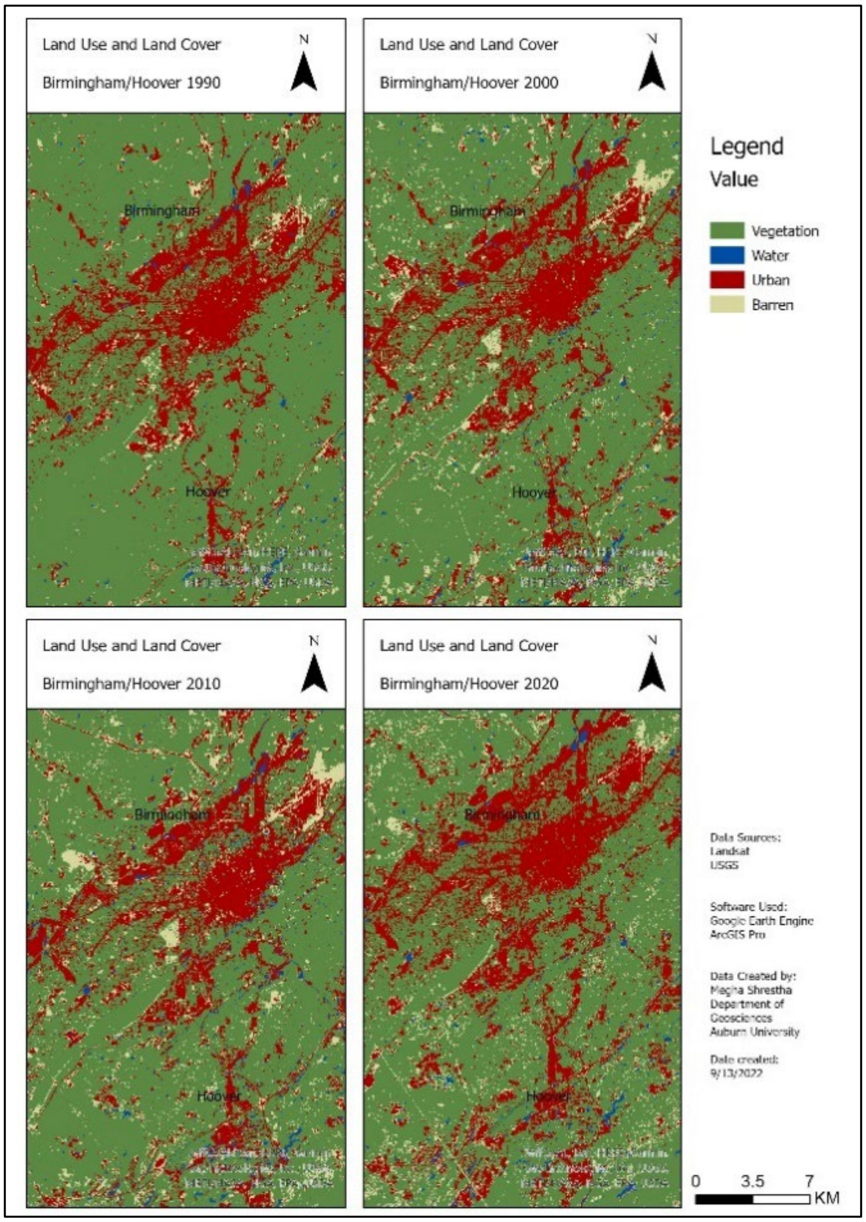


Figure 4.13: LUCC change of Birmingham.

Montgomery

Montgomery is the capital of Alabama. The city started growing at the intersection of I-65 and I-85 in 1990. Since then, it has spread towards the east and south. Gradually Montgomery took the form of a grid (Rodrigue 2013) and gradually filled in over the years. Based on Table 4.7 Montgomery added 54.79% of urban areas from 1990 to 2020 (Figure 4.8).

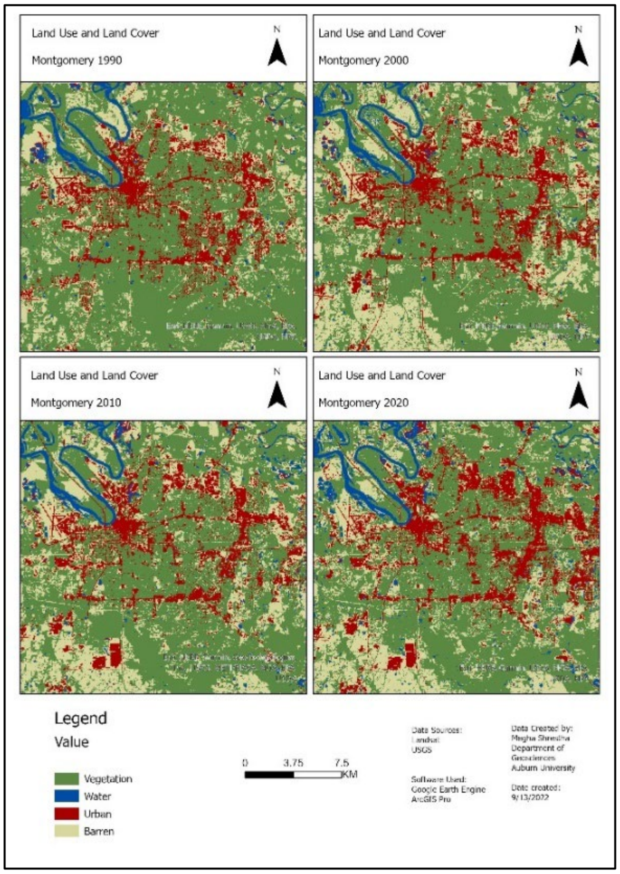


Figure 4.14: LUCC change of Montgomery

Dothan

Urban expansion of Dothan, on the other hand, mainly followed a radial pattern. It spread from the central part to periphery of the study area along US highways 431, 231 and 84 and state highways 1 and 53 (Figure 4.9). This kind of expansion is mainly the consequences of centrifugal forces (Colby 1933). In 1990, the concentration was in mainly the central part of the study area. From 2000, it started to spread towards periphery along several transportation routes. The net addition of urban built area was the highest for Dothan among the cities, resulting in 284.76% net addition from 1990 to 2020.

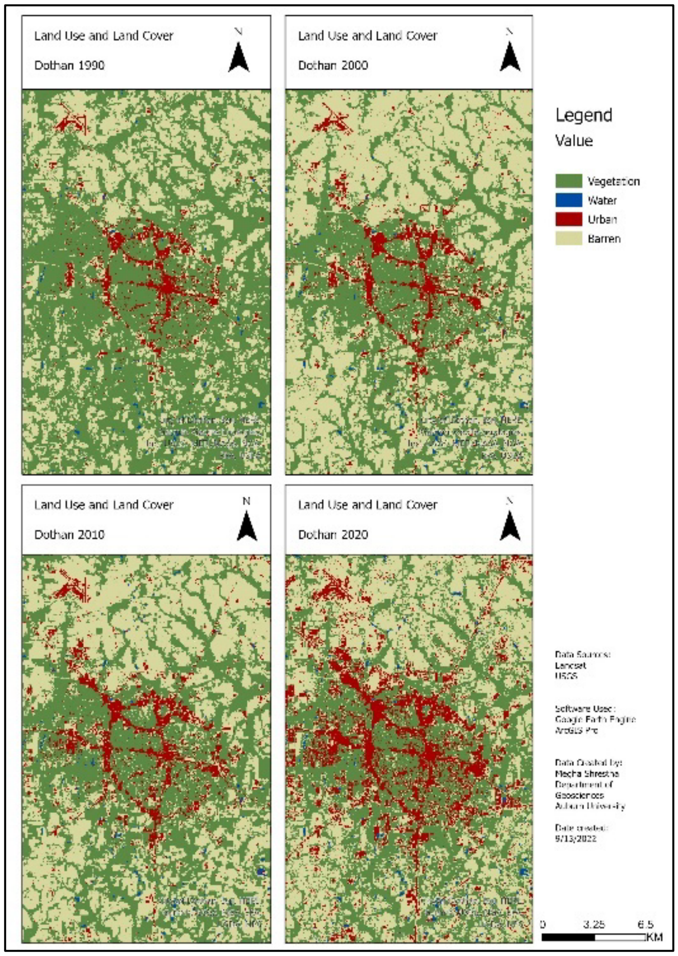
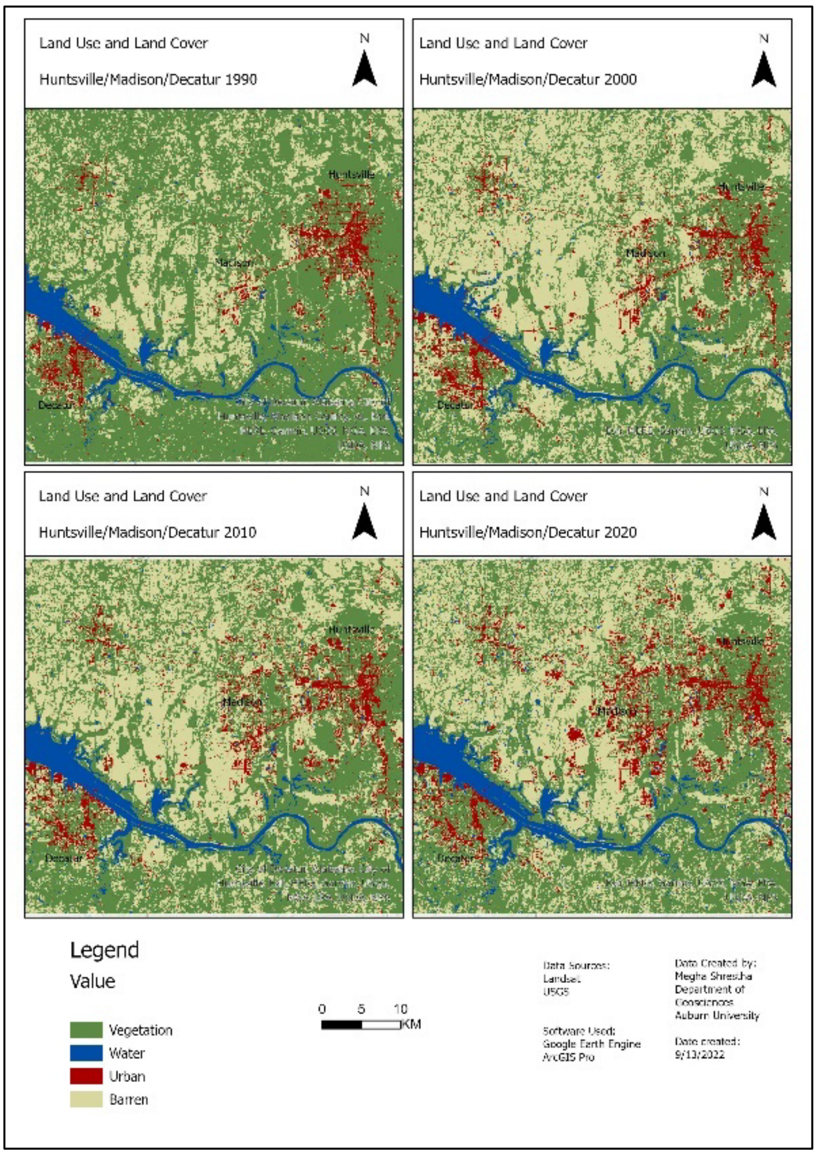


Figure 4.15: LUCC change of Dothan

Huntsville, Madison, and Decatur

Huntsville, Madison, and Decatur are three nearby cities. All of these cities have seen significant growth but along different driver variables. According to Table 4.7, the net addition of urban area from Huntsville, Madison, and Decatur was 91.50% from 1990 to 2020. Spatial expansion of urban or built-up areas of Huntsville in these three decades tends to follow major transportation routes and is highly concentrated in central and western part of the study area. For Madison, in 1990 urban built-up areas were mainly concentrated near I-565. From 2000, it started to spread towards the north. In 2010, it dispersed all over the study area (Figure 4.10 right). It is noticeable from Figure 4.10 that urban growth of Decatur was along water bodies. In 1990, urban expansion was limited to the river side (Tennessee River) and along I-65 which runs in a north to south direction with some in the western side of the I-65. From 2000 we can see growth in all directions. Not much of the water bodies were transformed to built-up (Table 4.9),



the expansion was beyond the river (Figure 4.10).

Figure 4.16: LUCC change of Huntsville, Madison, and Decatur

Mobile

Mobile urban area mainly situated near the banks of several rivers (Alabama River, Mobile River, Tombigbee River). Initially it grew near the rivers and later it spread from east to west (Figure 4.11). Mobile shrunk 2.7 % in terms of population from 1982 to 2010. But its urban built-up area increased significantly which highlights urban expansion or sprawl. The net addition to urban built-up was 130 % which is quite high (Table 4.7).

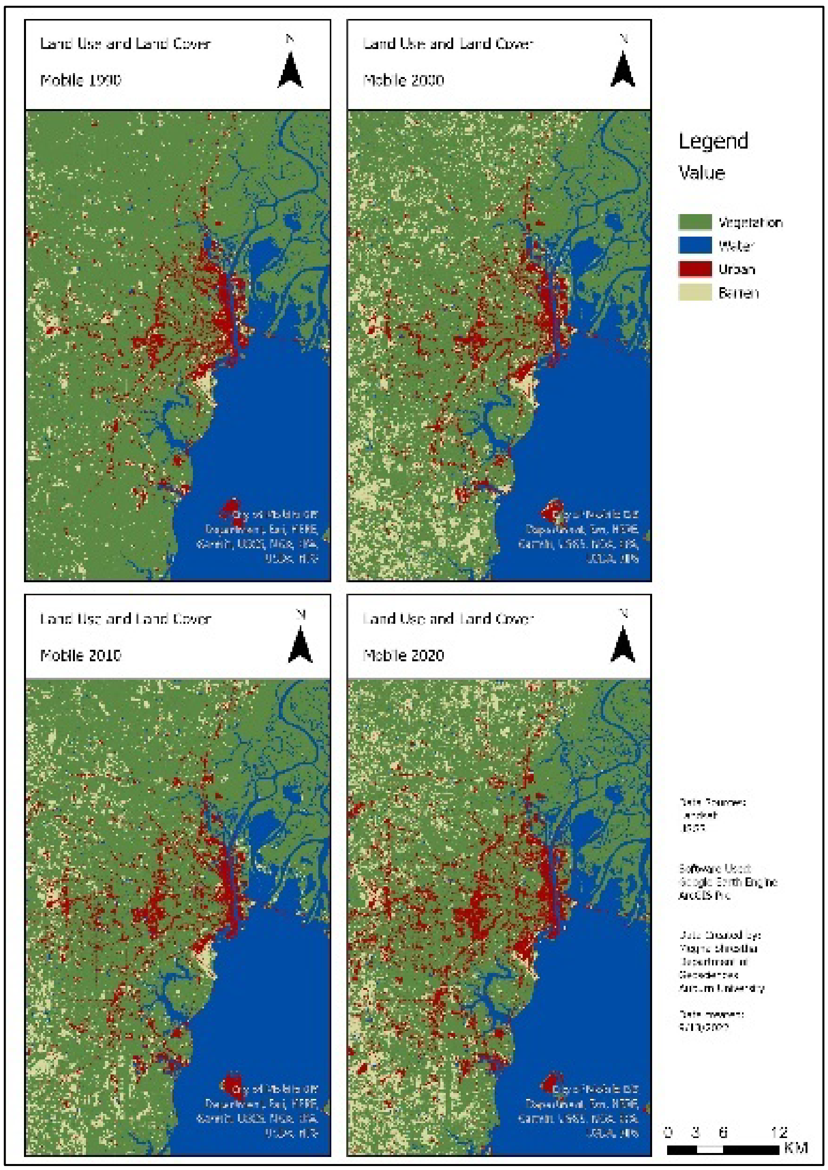
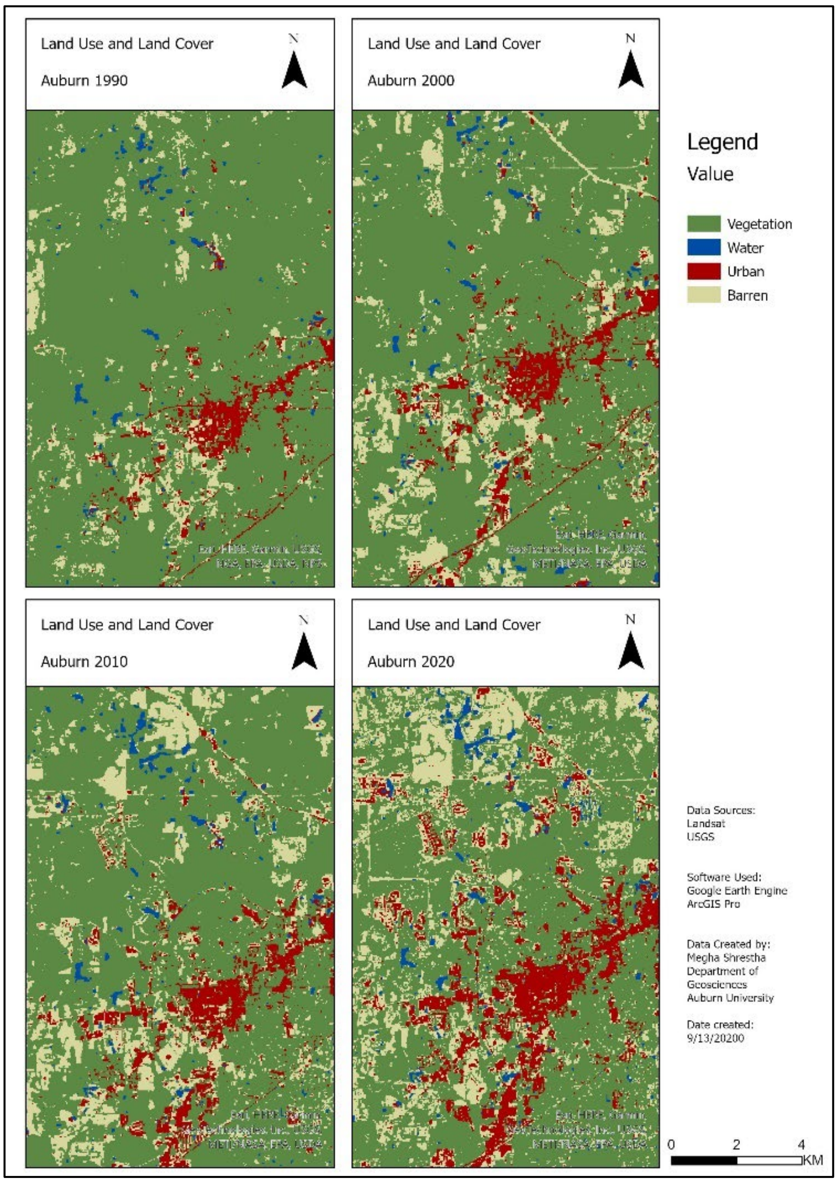


Figure 4.17: LUCC change of Mobile

Auburn

Based on Figure 4.12, urban built-up expansion for Auburn mainly follows north-east to south-west direction. From 1990 to 2010, it has taken place both side of I-85. Urban expansion is mainly concentrated in the central place of study area (due to presence of urban functions, one of the main being the presence of Auburn University) and expansion was more southern part than the northern part (Figure 4.12). In 1990, total urban built-up area was approximately 1.42 % and

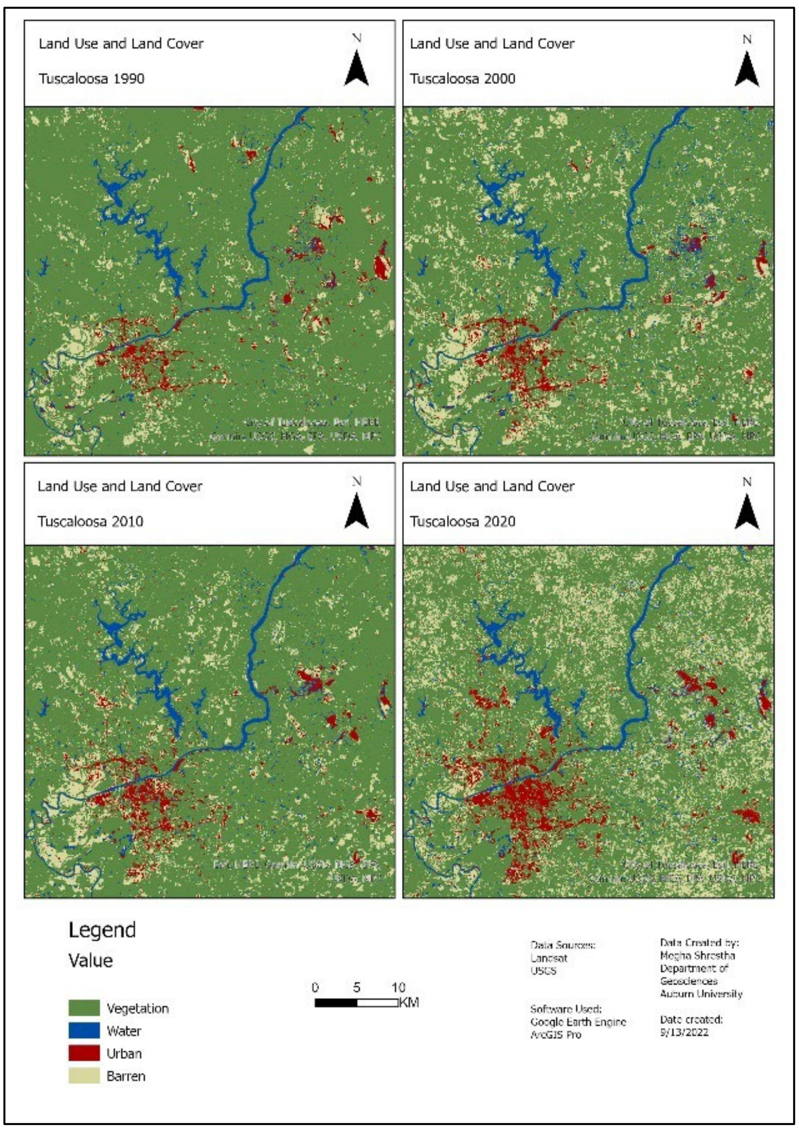


in 2020, it was 5.38 % (Table 4.7). So, the net addition was over 199 %.

Figure 4.18: LUCC change of Auburn.

Tuscaloosa

Tuscaloosa has similar urban function as Auburn city with University of Alabama as the central growth pivot, experienced spatial expansion of urban built-up area around a water body (Black Warrior River). Most of the expansion occurred south of the water body (Figure 4.13). It did not follow any significant transportation route. From 1990 to 2010, water bodies decreased gradually although built-up did not increase significantly. The net addition in these 10 years was



108.96 % for Tuscaloosa urban area (Table 4.7).

Figure 4.19: LUCC change of Tuscaloosa.

There are two adjacent urbanized areas. One is Birmingham and Hoover and another one is Huntsville and Madison. Though Birmingham is losing population, Hoover is gaining but for urban expansion both are gaining at a different rate. Hoover and Madison have developed as extension satellite cities of Birmingham and Huntsville respectively.

This study also reveals more conversions in certain categories. Mostly the non-urban category of LUCC has been encroached by urban built-up area (Table 4.10). One of the main focuses of this study was urban expansion of small and medium-sized areas. Birmingham, Tuscaloosa, and Montgomery are the three largest urban areas in Alabama and have shown steady growth, as opposed to the excessive growth in the mid-sized urban areas (Auburn, Dothan, and Hoover).

Accuracy Assessment of Classified Images

Because of the limited availability of ground truth data, it was impossible to perform accuracy assessment for all images with authenticity. Therefore, the strategy adopted to assess the accuracy is to calculate it using stratified random sampling method and Kappa statistics. The Kappa statistic is a "discrete multivariate technique used in accuracy assessment" (Yang 2002; Jensen 2007). Kappa analysis produces the K^ statistic, which approximates the Kappa. It measures the accuracy or harmony connecting the classification map from remotely sensed data, and the reference data specified the chance agreement and the major diagonal, which is specified by the column and row totals (Yang 2002; Jensen 2007).

Results (Table 4.8) revealed that overall accuracy met the minimum 92% accuracy level which was determined by the Anderson image classification scheme (Anderson et al. 2006).

Various literatures mentioned that the 'vegetation' land cover type caused most of the error because it contains different types of landuse (Table 4.9) (Yang 2002; Trousdale 2010)

Table 4.31:Accuracy Assessment and Kappa Statistics of Classified Image (1990, 200, 2010, 2020, and 2021).

City		1990			
		Vegetation	Water	Urban	Barren
Auburn	Vegetation	65	0	2	0
	Water	0	63	0	1
	Urban	0	0	62	0
	Barren	0	0	4	11
	Overall Accuracy	96.63%	Kappa Statistics	0.96634	
Tuscaloosa	Urban	70	0	0	0
	Vegetation	1	45	1	0
	Water	0	0	200	0
	Barren	0	0	0	0
	Overall Accuracy	99.37%	Kappa Statistics	0.9937	
Birmingham and Hoover	Urban	108	3	4	3
	Vegetation	1	89	3	0
	Water	1	5	335	2
	Barren	5	2	0	59
	Overall Accuracy	95.32%	Kappa Statistics	0.9532	
Dothan	Urban	76	0	1	1
	Vegetation	1	50	1	0
	Water	3	0	105	4
	Barren	2	0	2	24
	Overall Accuracy	94.44%	Kappa Statistics	0.94444	
Huntsville and Madison and Decatur	Urban	125	1	1	29
	Vegetation	0	130	3	1
	Water	2	2	255	5
	Barren	5	1	2	189
	Overall Accuracy	93.08%	Kappa Statistics	0.9308	

Mobile	Urban	53	0	1	0
	Vegetation	0	76	0	0
	Water	0	1	110	1
	Barren	0	2	1	22
	Overall Accuracy	97.75%	Kappa Statistics	0.9775	
Montgomery	Urban	63	0	1	1
	Vegetation	2	195	0	4
	Water	0	1	110	2
	Barren	3	2	1	79
	Overall Accuracy	96.34%	Kappa Statistics	0.9634	
			2000		
		Vegetation	Water	Urban	Barren
Auburn	Vegetation	67	0	2	0
	Water	0	60	0	1
	Urban	0	0	62	0
	Barren	0	0	4	11
	Overall Accuracy	96.63%	Kappa Statistics	0.9662	
Tuscaloosa	Urban	74	0	0	0
	Vegetation	1	49	1	0
	Water	0	0	200	0
	Barren	0	0	0	0
	Overall Accuracy	99.38%	Kappa Statistics	0.9938	
Birmingham and Hoover	Urban	110	0	4	3
	Vegetation	0	87	2	0
	Water	1	0	340	2
	Barren	5	0	0	59
	Overall Accuracy	97.23%	Kappa Statistics	0.9723	
Dothan	Urban	82	0	1	1
	Vegetation	1	52	1	0
	Water	0	0	107	2
	Barren	2	0	2	24

	Overall Accuracy	97.07%	Kappa Statistics	0.9707	
Huntsville and Madison and Decatur	Urban	127	1	1	29
	Vegetation	0	135	1	1
	Water	0	2	261	5
	Barren	5	0	2	190
	Overall Accuracy	93.82%	Kappa Statistics	0.9382	
Mobile	Urban	55	0	1	0
	Vegetation	0	81	0	0
	Water	0	1	101	1
	Barren	0	0	1	22
	Overall Accuracy	98.48%	Kappa Statistics	0.9848	
Montgomery	Urban	62	0	1	1
	Vegetation	2	200	0	4
	Water	0	1	107	2
	Barren	2	2	1	79
	Overall Accuracy	96.55%	Kappa Statistics	0.9655	
City	**2010**				
		Vegetation	Water	Urban	Barren
Auburn	Vegetation	40	0	1	2
	Water	0	46	0	0
	Urban	0	0	42	1
	Barren	0	0	3	10
	Overall Accuracy	95.17%	Kappa Statistics	0.9517	
Tuscaloosa	Urban	49	0	1	0
	Vegetation	1	35	0	0
	Water	2	1	116	0
	Barren	0	0	0	0
	Overall Accuracy	97.56%	Kappa Statistics	0.9756	
Birmingham and Hoover	Urban	61	0	5	5
	Vegetation	1	64	3	1
	Water	2	1	219	2

	Barren	6	0	1	33
	Overall Accuracy	93.32%	Kappa Statistics	0.9332	
Dothan	Urban	51	0	3	0
	Vegetation	2	25	2	0
	Water	0	0	77	0
	Barren	1	0	0	12
	Overall Accuracy	95.38%	Kappa Statistics	0.9538	
Huntsville and Madison and Decatur	Urban	76	0	2	20
	Vegetation	2	87	1	1
	Water	1	0	153	6
	Barren	3	0	0	157
	Overall Accuracy	92.93%	Kappa Statistics	0.9293	
Mobile	Urban	45	0	0	0
	Vegetation	2	62	0	0
	Water	0	0	63	1
	Barren	1	0	0	10
	Overall Accuracy	97.83%	Kappa Statistics	0.9783	
Montgomery	Urban	30	1	1	5
	Vegetation	0	131	2	2
	Water	0	2	87	1
	Barren	2	1	2	50
	Overall Accuracy	94.01%	Kappa Statistics	0.9401	
City	**2020**				
		Vegetation	Water	Urban	Barren
Auburn	Vegetation	36	0	0	1
	Water	0	36	1	0
	Urban	0	0	35	0
	Barren	1	0	3	8
	Overall Accuracy	95.04%	Kappa Statistics	0.9504	
Tuscaloosa	Urban	57	0	6	0
	Vegetation	1	32	4	0

	Water	0	2	130	0
	Barren	0	0	0	0
	Overall Accuracy	94.40%	Kappa Statistics	0.944	
Birmingham and Hoover					
	Urban	76	0	6	3
	Vegetation	2	58	4	2
	Water	3	2	232	1
	Barren	1	0	1	36
	Overall Accuracy	94.15%	Kappa Statistics	0.9415	
Dothan					
	Urban	57	0	2	2
	Vegetation	1	39	0	1
	Water	1	0	58	1
	Barren	1	0	3	18
	Overall Accuracy	93.48%	Kappa Statistics	0.9348	
Huntsville and Madison and Decatur					
	Urban	99	0	1	16
	Vegetation	1	82	0	0
	Water	1	1	167	8
	Barren	6	0	1	137
	Overall Accuracy	93.14%	Kappa Statistics	0.9314	
Mobile					
	Urban	43	0	1	2
	Vegetation	3	56	0	0
	Water	0	0	64	0
	Barren	1	0	5	4
	Overall Accuracy	93.30%	Kappa Statistics	0.933	
Montgomery					
	Urban	32	1	1	1
	Vegetation	1	113	0	5
	Water	0	2	76	2
	Barren	5	0	2	60
	Overall Accuracy	93.36%	Kappa Statistics	0.9336	

City	**2021**				
		Vegetation	Water	Urban	Barren
Auburn					
	Vegetation	36	0	0	1

	Water	0	37	0	0
	Urban	0	0	35	0
	Barren	1	0	3	8
	Overall Accuracy	95.87%	Kappa Statistics	0.9587	
Tuscaloosa	Urban	56	0	7	0
	Vegetation	1	35	1	0
	Water	0	2	130	0
	Barren	0	0	0	0
	Overall Accuracy	95.26%	Kappa Statistics	0.9526	
Birmingham and Hoover	Urban	74	0	5	6
	Vegetation	2	58	4	2
	Water	7	3	226	2
	Barren	3	0	0	35
	Overall Accuracy	92.04%	Kappa Statistics	0.9204	
Dothan	Urban	58	0	2	1
	Vegetation	1	39	0	1
	Water	1	0	58	1
	Barren	0	0	2	20
	Overall Accuracy	95.11%	Kappa Statistics	0.9511	
Huntsville and Madison and Decatur	Urban	91	0	3	22
	Vegetation	1	82	0	0
	Water	0	0	169	8
	Barren	6	0	3	125
	Overall Accuracy	91.57%	Kappa Statistics	0.9157	
Mobile	Urban	44	0	1	1
	Vegetation	2	57	0	0
	Water	0	0	64	0
	Barren	2	0	5	3
	Overall Accuracy	93.85%	Kappa Statistics	0.9385	
Montgomery	Urban	30	0	0	5
	Vegetation	5	109	0	5

Water	0	3	75	2
Barren	3	0	3	61
Overall Accuracy	91.36%	Kappa Statistics	0.9136	

Change Analysis

A change analysis was performed during the period 2010-2020 for each city. Each of the 10 cities experienced loss in non-urban areas and an increase in urban areas during 2010-2020. Auburn, Tuscaloosa, and Dothan saw the greatest increase in urban areas during 2010-2020 leading to 1118, 3915, and 3715 ha which accounted for 35.22%, 36.83%, and 54.09% increase in urban areas in 10 years (Table 4.9).

Table 4.32: Gains, losses, net change (ha), and net change (%) for the different land use and land cover for all 10 cities for 2010-2020

City	Class	2010-2020			
		Gains (ha)	Losses (ha)	Net change (ha)	Net Change (%)
Auburn					
	Urban	1491	374	1118	35.22
	Vegetation	2750	9859	-7108	13.81
	Water	228	75	153	-18.85
	Barren	9172	3290	5837	34.39
Tuscaloosa					
	Urban	5117	1201	3915	36.83
	Vegetation	9554	34885	-25331	-18.64
	Water	1283	1475	-192	-2.49
	Barren	32212	10605	21607	48.62
Birmingham and Hoover					
	Urban	9768	3634	6134	21.48
	Vegetation	12457	39425	-26968	-12.38
	Water	1566	1428	138	2.38
	Barren	33943	13246	20696	40
Dothan					
	Urban	4163	449	3715	54.09
	Vegetation	4068	5612	-1544	-5.77
	Water	242	93	150	25.28
	Barren	4541	6861	-2320	-7.43

Huntsville and Madison and Decatur					
	Urban	8096	3614	4482	22.59
	Vegetation	18082	25772	-7690	-5.32
	Water	3246	487	2758	16.14
	Barren	22820	22370	450	0.39
Mobile					
	Urban	6494	1922	4573	28.48
	Vegetation	6102	17785	-11683	-10.66
	Water	1684	1141	543	1.00
	Barren	13381	6814	6567	24.39
Montgomery					
	Urban	3558	1678	1881	19.50
	Vegetation	6229	9295	-3066	-5.68
	Water	1215	303	912	18.27
	Barren	7891	7618	273	0.76

Table 4.9 indicates that during 2010-2020 there was 21.48% and 22.59% net change in Birmingham and Hoover, and Huntsville, Madison, and Decatur. It was highest for Dothan (54.0%) and lowest for Montgomery (19.5%). Some of the 'water' category has also changed to urban land use. As a result, urban built-up increased continuously and the water and non-urban category decreased gradually for all cities.

Table 4.10 represents the contributors to the net change in percentage for each land use type used in the classification for the different cities. It is seen from the table that the biggest contributor for land use change to urban is the non-urban area (vegetation and barren) for each of the cities. Dothan is experiencing the biggest change in area from non-urban to urban combined. Table 4.10 also shows that mostly all other LUCC was converted to urban built-up areas, but the rate of change varied from city to city. The 'non-urban' category here includes vacant land as categorized as barren LUCC and various types of vegetation; thus, it is understandable why this transition is most common. Urban built-up areas mostly remained unchanged since it is very unusual to convert built-up areas to vegetation or water body.

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Table 4.33: Contributors to the net change in area for each land use type for all 10 cities in ha (2010-2015)

City	**2010-2020**				
	Contributors (in %)				
Auburn		Urban	Vegetation	Water	Barren
	Urban	0.00	1.17	2.24	5.52
	Vegetation	-25.54	0.00	-12.83	-58.02
	Water	1.04	0.27	0.00	0.08
	Barren	-29.87	14.41	-0.95	0.00
Tuscaloosa					
	Urban	0.00	1.19	2.12	8.01
	Vegetation	-28.58	0.00	-3.45	-101.35
	Water	-2.50	0.17	0.00	-1.30
	Barren	-27.24	14.36	3.75	0.00
Birmingham and Hoover					
	Urban	0.00	1.41	5.65	7.6
	Vegetation	-15.41	0.00	-9.01	-74.11
	Water	-1.42	0.21	0.00	-0.17
	Barren	-10.53	9.39	0.92	0.00
Dothan					
	Urban	0.00	3.62	-8.77	8.13
	Vegetation	-32.55	0.00	-26.40	-1.20
	Water	1.23	0.41	0.00	-0.02
	Barren	-86.48	1.42	1.34	0.00
Huntsville and Madison and Decatur					
	Urban	0.00	0.47	-1.56	3.44
	Vegetation	-4.69	0.00	-14.37	-4.24
	Water	1.45	1.35	0.00	0.41

	Barren	-25.94	3.23	-3.32	0.00
Mobile					
	Urban	0.00	2.20	0.13	8.98
	Vegetation	-23.27	0.00	-1.10	-41.36
	Water	-0.63	0.49	0.00	0.12
	Barren	-15.91	6.94	-0.05	0.00
Montgomery					
	Urban	0.00	1.23	-6.8	4.08
	Vegetation	-9.07	0.00	-11.41	-5.33
	Water	3.57	0.82	0.00	0.48
	Barren	-18.72	3.32	-4.15	0.00

Transition Potential for the cities

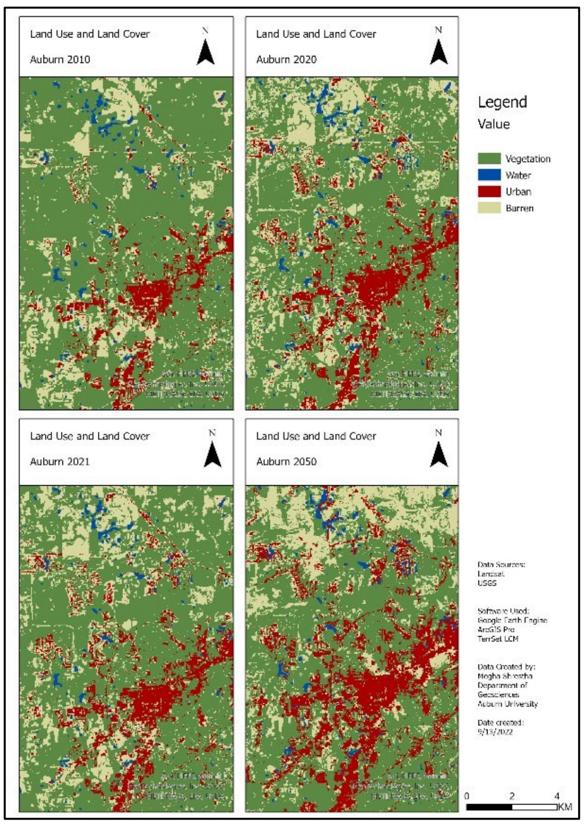
The transition potential maps for each city are created for all four transitions: toUrban, toVegetaion, toWater, and toBarren using the MLP neural network to predict the LUCC change for 2050. The transition probabilities were calculated using the Markov chain using the six driving variables shown in Figure 4.5 for Mobile, AL. The modeler also reports on the model's accuracy and ability in predicting whether the validation pixels will adjust and, if so, to which class. The accuracy calculated minus the accuracy expected by change is the skill measure. Table 4.11 shows the model skill measure and accuracy rate to urban sub-model for each of the 10 cities.

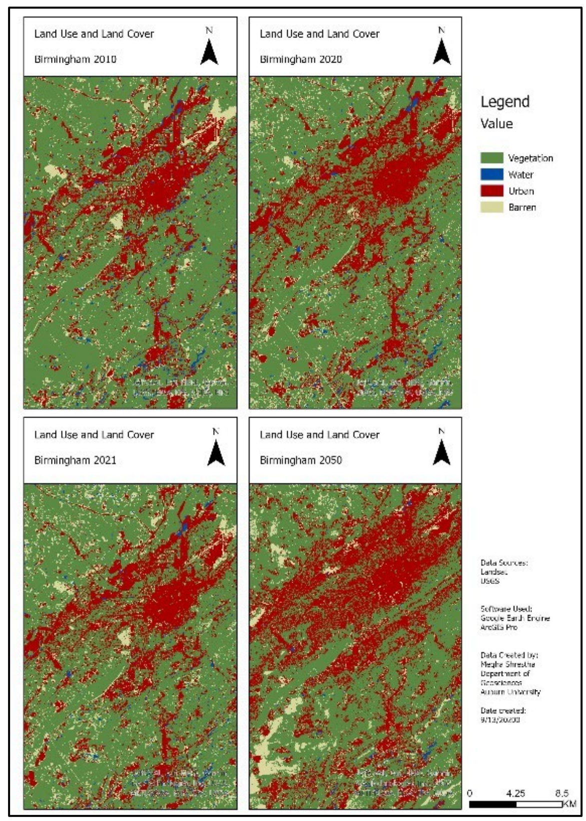
Table 4.34: Model skill breakdown for all driving variable for all 10 cities for modeling change to urban areas sub model

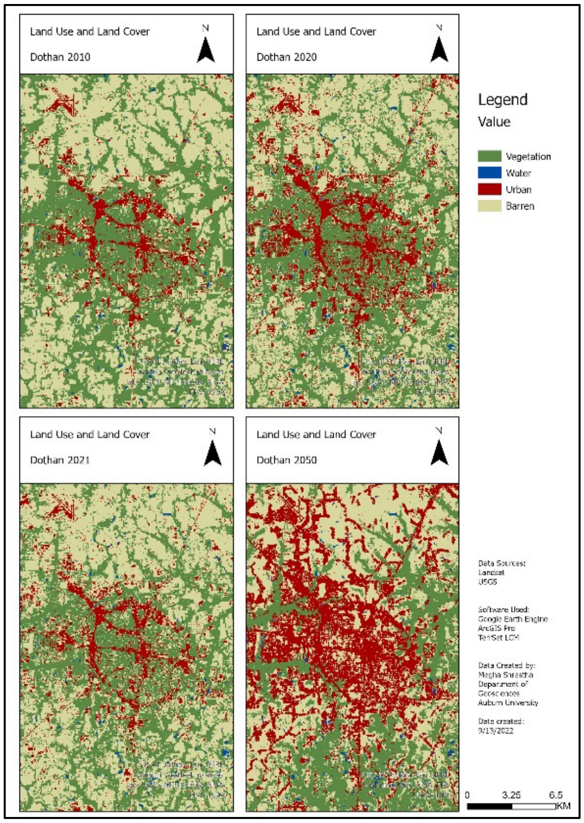
City	Skill Measure	Accuracy Rate (%)
Auburn	0.6393	72.95
Tuscaloosa	0.3412	50.59
Birmingham and Hoover	0.6703	72.52
Dothan	0.65	73.75
Huntsville and Madison and Decatur	0.6275	72.06
Mobile	0.5489	66.17
Montgomery	0.6692	75.19

Future Urban Built-up Expansion

Based on these factors, the predicted LUCC of 2050 was produced for all the 10 cities of Alabama. The 2050 growth projections in table 8 indicate that built up area for all 10 cities of Alabama will continue to grow at a fast rate. Figure 4.14 shows the LUCC classification (2010-2020) and land cover projection (2050) for all 10 cities in Alabama. There is a significant increase of urban area from 2020 to 2050 with business-as-usual scenario as shown in Figure 4.14.






Land Use and Land Cover
Dothan 2010
Land Use and Land Cover
Dothan 2020
Land Use and Land Cover
Dothan 2021
Land Use and Land Cover
Dothan 2050
N
Legend
Value
Vegetation
Water
Urban
Barren
Data Sources:
Landsat
USGS
Software Used:
Google Earth Engine
ArcGIS Pro
TerrSet LCM
Data Created by:
Megha Shrestha
Department of
Geosciences
Auburn University
Date created:
9/13/2022
0 3.25 6.5
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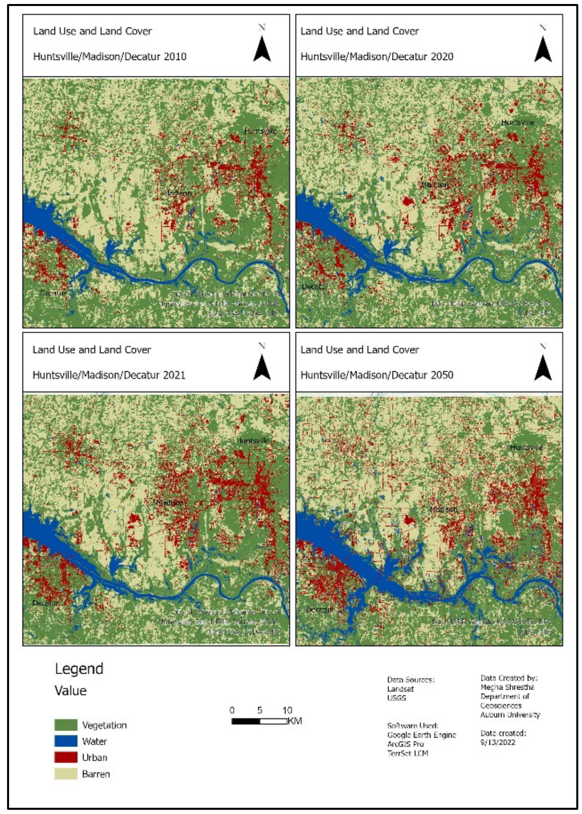
Land Use and Land Cover
Huntsville/Madison/Decatur 2010
Land Use and Land Cover
Huntsville/Madison/Decatur 2020
Land Use and Land Cover
Huntsville/Madison/Decatur 2021
Land Use and Land Cover
Huntsville/Madison/Decatur 2050
N
Legend
Value
Vegetation
Water
Urban
Barren
0 5 10
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Data Sources:
Landsat
USGS
Software Used:
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Data Created by:
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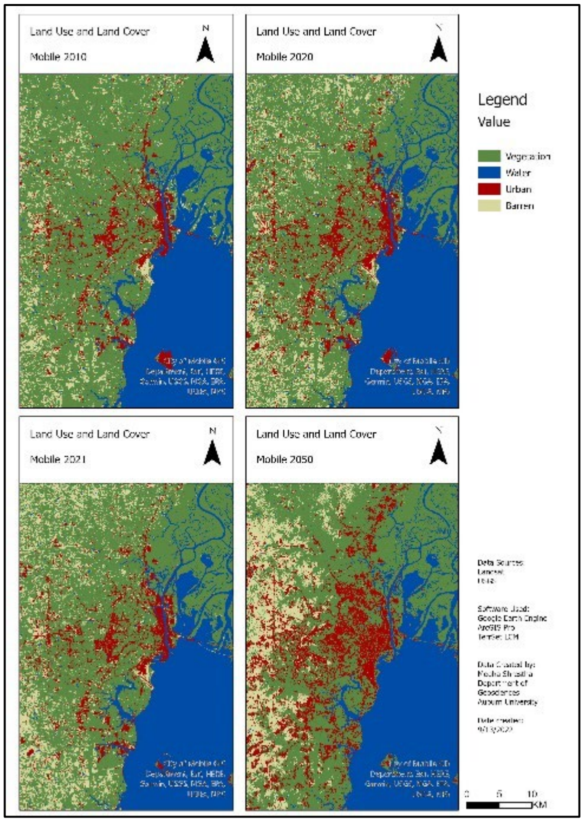
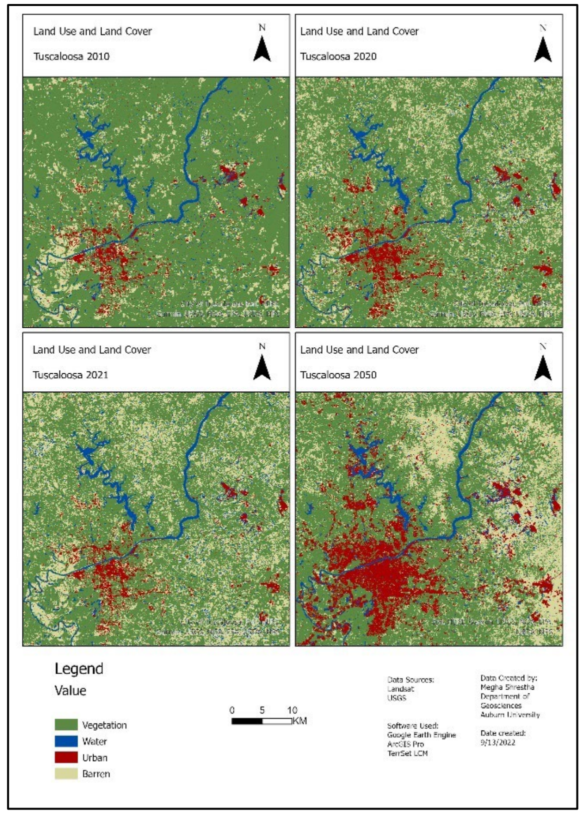
Department of
Geosciences
Auburn University
Date created:
9/13/2022



Land Use and Land Cover
Mobile 2010
N
Land Use and Land Cover
Mobile 2020
N
Land Use and Land Cover
Mobile 2021
N
Land Use and Land Cover
Mobile 2050
N
Legend
Value
Vegetation
Water
Urban
Barren
Data Sources:
Software Used:
Google Earth Engine
ArcGIS Pro
Data Created by:
Auburn University
0 5 10
KM



Land Use and Land Cover
Tuscaloosa 2010
N
Land Use and Land Cover
Tuscaloosa 2020
N
Land Use and Land Cover
Tuscaloosa 2021
N
Land Use and Land Cover
Tuscaloosa 2050
N
Legend
Value
Vegetation
Water
Urban
Barren
0 5 10
KM
Data Sources:
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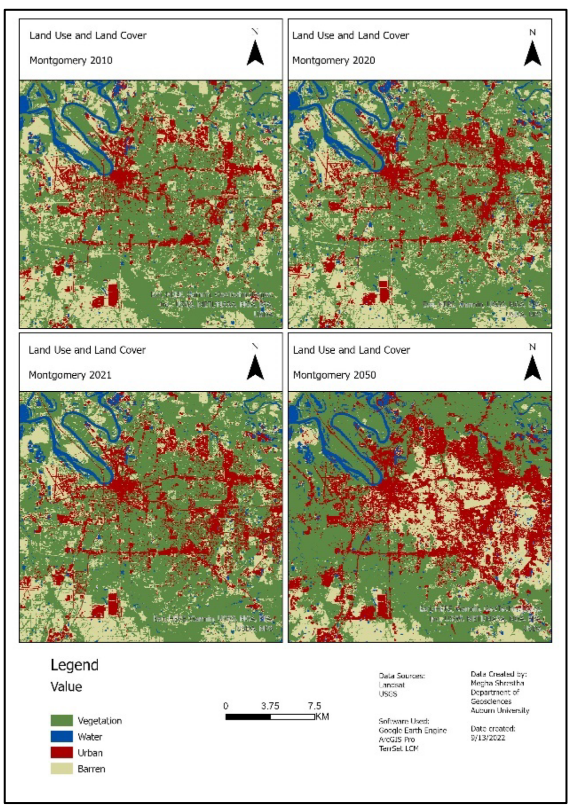

Land Use and Land Cover
Montgomery 2010
N
Land Use and Land Cover
Montgomery 2020
N
Land Use and Land Cover
Montgomery 2021
N
Land Use and Land Cover
Montgomery 2050
N
Legend
Value
Vegetation
Water
Urban
Barren
0 3.75 7.5
KM
Data Sources:
Landsat
USGS
Software Used:
Google Earth Engine
ArcGIS Pro
TerrSet LCM
Data Created by:
Megha Shrestha
Department of
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Auburn University
Date created:
9/13/2022

Figure 4.20: Predicted Urban Built-up Expansion, 2050 for all 10 cities.

From Table 4.12, the projected 2050 urban built-up area shows a significant increase in its land cover percentage. The growth projections for 2050 show that Montgomery will have an increase of 9828 ha. The two neighboring cities of Birmingham and Hoover will increase by 25614 ha. Similar trend is seen for the neighboring cities of Huntsville and Madison and Decatur projecting an increase of 12854 ha. The model output projected 15618 ha increase for Mobile, 21085 ha for Tuscaloosa, 12267 ha for Dothan, 9828 ha for Montgomery and 4237 ha for Auburn.

Table 4.35: Predicted Urban Built-up by 2050.

Study Area	**LULC**	**Area 2010 (hectares)**	**Area 2050 (hectares)**	**Difference**		**Annual rate of change (2010-2050) in %**
				Hectares	**(%)**	
Auburn	Urban built-up	2056	6293	4237	206	2.84
Tuscaloosa	Urban built-up	6715	27800	21085	314	3.62
Birmingham and Hoover	Urban built-up	22416	48030	25614	114	1.92
Dothan	Urban built-up	3154	15421	12267	389	4.05
Huntsville and Madison and Decatur	Urban built-up	15361	28215	12854	84	1.53
Mobile	Urban built-up	11486	27104	15618	136	2.17
Montgomery	Urban built-up	7766	17594	9828	127	2.07

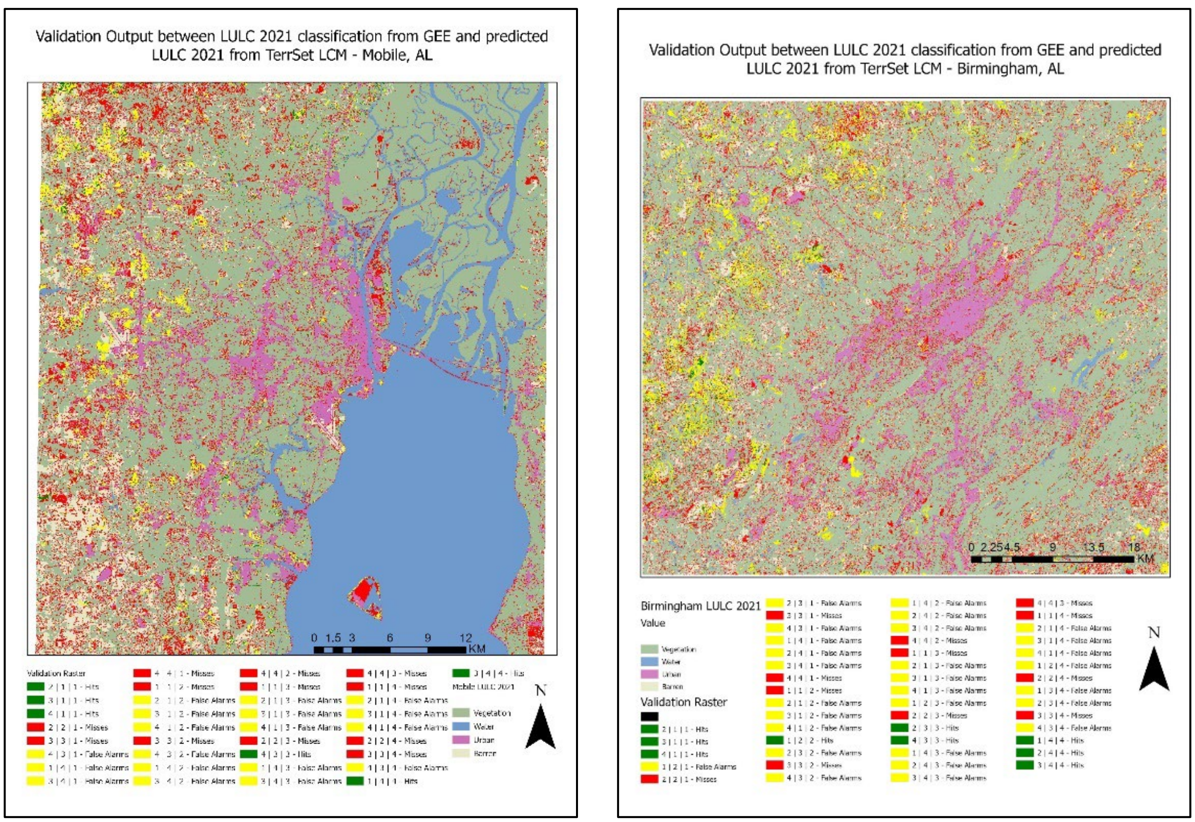
Annual future growth in percentage will be the highest in Dothan with 4.05% (2010-2050) (Table 4.12). Auburn will grow fast (2.84% annual change rate 2010-2050). Birmingham and Hoover will grow at a rate of 1.92% (2010-2050). All these 10 cities will see a significant growth in urban areas in the next 40 years compared to 2010.

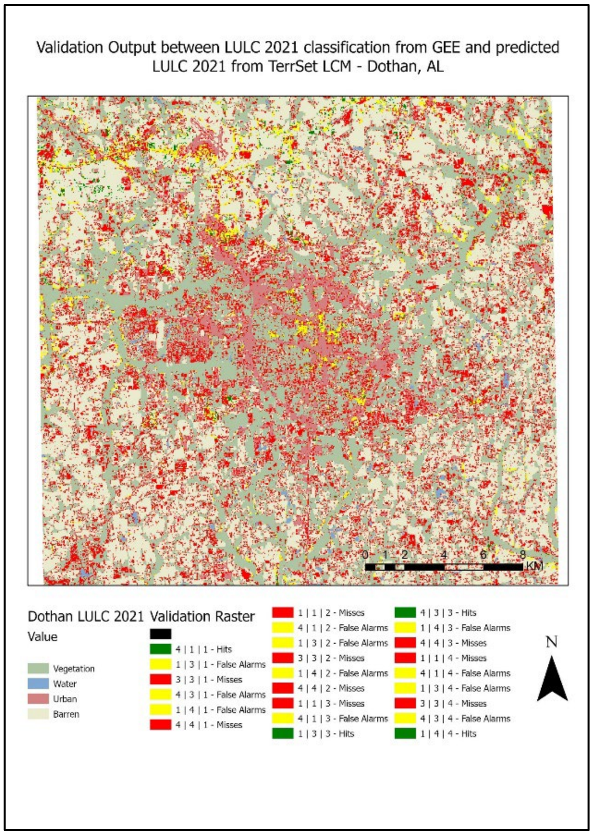
Future prediction for 2050 showed that only Auburn will grow faster in the next 30 years

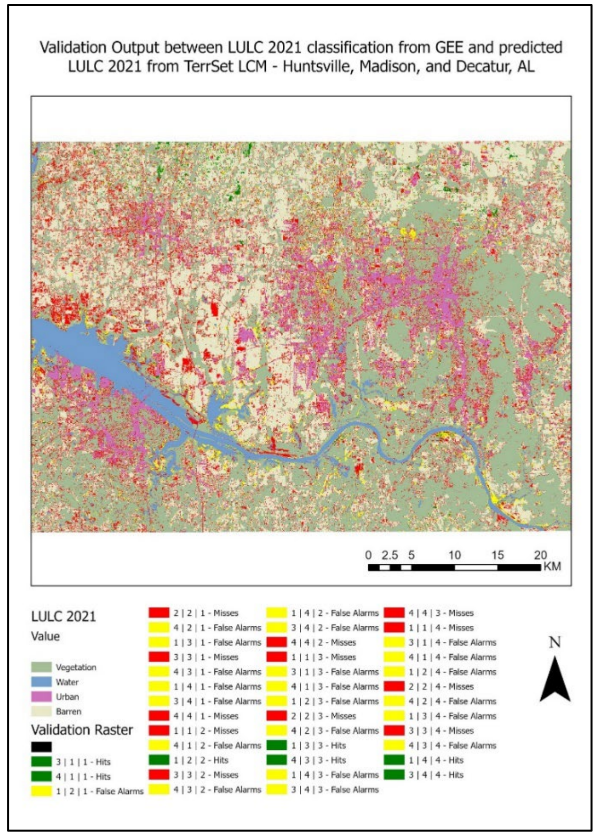
(105.93 ha annually) compared to last 30 years (70.06 ha annually). On the other hand, Madison, Hoover, Birmingham, and Mobile will grow at a slower pace in the future than in the past.

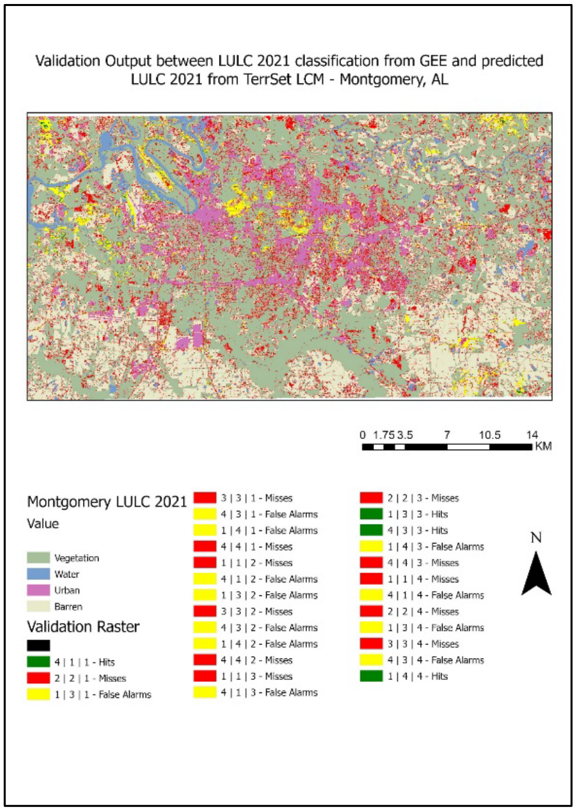
Validation of future growth scenarios

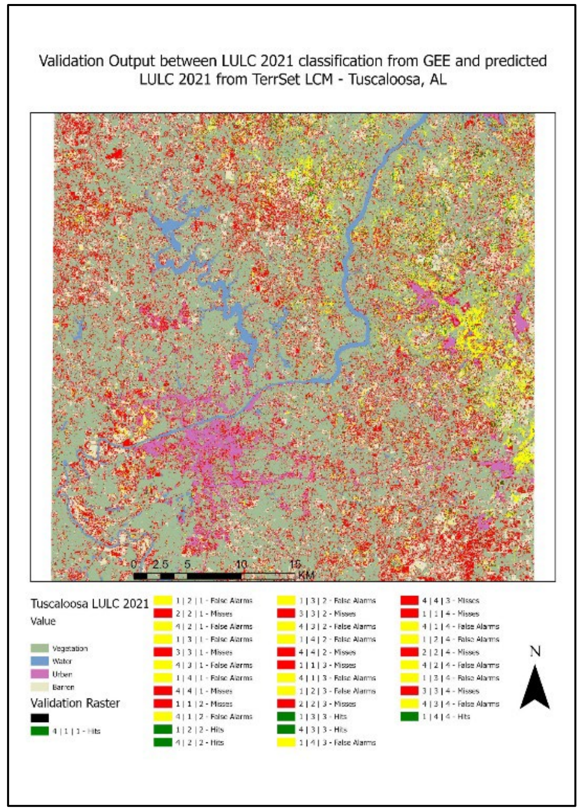
The inbuilt validation module of the TerrSet software was used to validate the result of the prediction. 2021 imagery was classified beforehand with accuracy assessment shown in Table 4.8. The CA Markov model inside the LCM was then used to predict the land-use classification for 2021 using the same driver variables used to predict for 2050. The results were then compared using the model validation module inside the change prediction tab of the LCM. It provides a raster with hits, misses, and false alarms for each of the landuse conversions for all 10 SMSC of Alabama (Figure 4.15).




Validation Output between LULC 2021 classification from GEE and predicted LULC 2021 from TerrSet LCM - Dothan, AL
0 1 2 4 6 8 KM
Dothan LULC 2021
Value
Vegetation
Water
Urban
Barren
Validation Raster
4 | 1 | 1 - Hits
1 | 3 | 1 - False Alarms
3 | 3 | 1 - Misses
4 | 3 | 1 - False Alarms
1 | 4 | 1 - False Alarms
4 | 4 | 1 - Misses
1 | 1 | 2 - Misses
4 | 1 | 2 - False Alarms
1 | 3 | 2 - False Alarms
3 | 3 | 2 - Misses
1 | 4 | 2 - False Alarms
4 | 4 | 2 - Misses
1 | 1 | 3 - Misses
4 | 1 | 3 - False Alarms
1 | 3 | 3 - Hits
4 | 3 | 3 - Hits
1 | 4 | 3 - False Alarms
4 | 4 | 3 - Misses
1 | 1 | 4 - Misses
4 | 1 | 4 - False Alarms
1 | 3 | 4 - False Alarms
3 | 3 | 4 - Misses
4 | 3 | 4 - False Alarms
1 | 4 | 4 - Hits
N


Validation Output between LULC 2021 classification from GEE and predicted LULC 2021 from TerrSet LCM - Huntsville, Madison, and Decatur, AL
0 2.5 5 10 15 20 KM
LULC 2021
Value
Vegetation
Water
Urban
Barren
Validation Raster
3 | 1 | 1 - Hits
4 | 1 | 1 - Hits
1 | 2 | 1 - False Alarms
2 | 2 | 1 - Misses
4 | 2 | 1 - False Alarms
1 | 3 | 1 - False Alarms
3 | 3 | 1 - Misses
4 | 3 | 1 - False Alarms
1 | 4 | 1 - False Alarms
3 | 4 | 1 - False Alarms
4 | 4 | 1 - Misses
1 | 1 | 2 - Misses
4 | 1 | 2 - False Alarms
1 | 2 | 2 - Hits
3 | 3 | 2 - Misses
4 | 3 | 2 - False Alarms
1 | 4 | 2 - False Alarms
3 | 4 | 2 - False Alarms
4 | 4 | 2 - Misses
1 | 1 | 3 - Misses
3 | 1 | 3 - False Alarms
4 | 1 | 3 - False Alarms
1 | 2 | 3 - False Alarms
2 | 2 | 3 - Misses
4 | 2 | 3 - False Alarms
1 | 3 | 3 - Hits
4 | 3 | 3 - Hits
1 | 4 | 3 - False Alarms
3 | 4 | 3 - False Alarms
4 | 4 | 3 - Misses
1 | 1 | 4 - Misses
3 | 1 | 4 - False Alarms
4 | 1 | 4 - False Alarms
1 | 2 | 4 - False Alarms
2 | 2 | 4 - Misses
4 | 2 | 4 - False Alarms
1 | 3 | 4 - False Alarms
3 | 3 | 4 - Misses
4 | 3 | 4 - False Alarms
1 | 4 | 4 - Hits
3 | 4 | 4 - Hits
N


Validation Output between LULC 2021 classification from GEE and predicted LULC 2021 from TerrSet LCM - Montgomery, AL
0 1.75 3.5 7 10.5 14
KM
Montgomery LULC 2021
Value
Vegetation
Water
Urban
Barren
Validation Raster
4 | 1 | 1 - Hits
2 | 2 | 1 - Misses
1 | 3 | 1 - False Alarms
3 | 3 | 1 - Misses
4 | 3 | 1 - False Alarms
1 | 4 | 1 - False Alarms
4 | 4 | 1 - Misses
1 | 1 | 2 - Misses
4 | 1 | 2 - False Alarms
1 | 3 | 2 - False Alarms
3 | 3 | 2 - Misses
4 | 3 | 2 - False Alarms
1 | 4 | 2 - False Alarms
4 | 4 | 2 - Misses
1 | 1 | 3 - Misses
4 | 1 | 3 - False Alarms
2 | 2 | 3 - Misses
1 | 3 | 3 - Hits
4 | 3 | 3 - Hits
1 | 4 | 3 - False Alarms
4 | 4 | 3 - Misses
1 | 1 | 4 - Misses
4 | 1 | 4 - False Alarms
2 | 2 | 4 - Misses
1 | 3 | 4 - False Alarms
3 | 3 | 4 - Misses
4 | 3 | 4 - False Alarms
1 | 4 | 4 - Hits
N


Validation Output between LULC 2021 classification from GEE and predicted LULC 2021 from TerrSet LCM - Tuscaloosa, AL
0 2.5 5 10 15
KM
Tuscaloosa LULC 2021
Value
Vegetation
Water
Urban
Barren
Validation Raster
4 | 1 | 1 - Hits
1 | 2 | 1 - False Alarms
2 | 2 | 1 - Misses
4 | 2 | 1 - False Alarms
1 | 3 | 1 - False Alarms
3 | 3 | 1 - Misses
4 | 3 | 1 - False Alarms
1 | 4 | 1 - False Alarms
4 | 4 | 1 - Misses
1 | 1 | 2 - Misses
4 | 1 | 2 - False Alarms
1 | 2 | 2 - Hits
4 | 2 | 2 - Hits
1 | 3 | 2 - False Alarms
3 | 3 | 2 - Misses
4 | 3 | 2 - False Alarms
1 | 4 | 2 - False Alarms
4 | 4 | 2 - Misses
1 | 1 | 3 - Misses
4 | 1 | 3 - False Alarms
1 | 2 | 3 - False Alarms
2 | 2 | 3 - Misses
1 | 3 | 3 - Hits
4 | 3 | 3 - Hits
1 | 4 | 3 - False Alarms
4 | 4 | 3 - Misses
1 | 1 | 4 - Misses
4 | 1 | 4 - False Alarms
1 | 2 | 4 - False Alarms
2 | 2 | 4 - Misses
4 | 2 | 4 - False Alarms
1 | 3 | 4 - False Alarms
3 | 3 | 4 - Misses
4 | 3 | 4 - False Alarms
1 | 4 | 4 - Hits
N

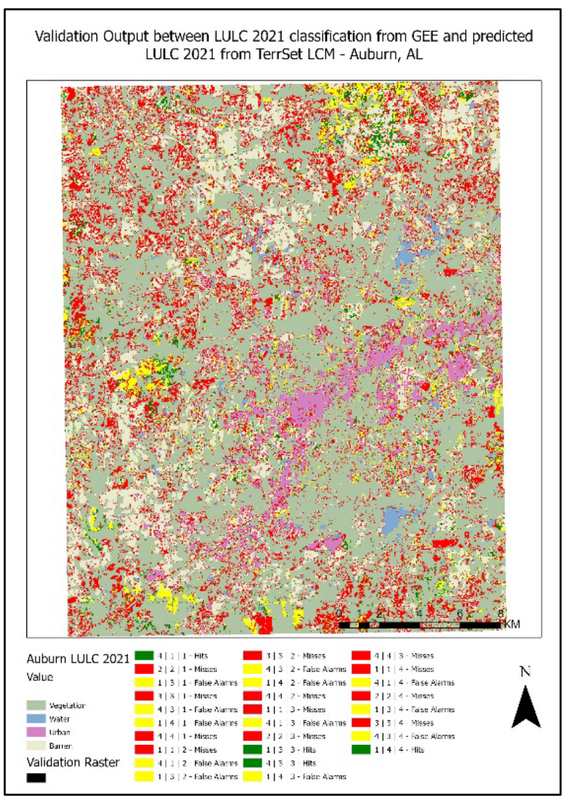

Validation Output between LULC 2021 classification from GEE and predicted LULC 2021 from TerrSet LCM - Auburn, AL
0 1 2 4 6 8
KM
Auburn LULC 2021
Value
Vegetation
Water
Urban
Barren
Validation Raster
4 | 1 | 1 - Hits
2 | 2 | 1 - Misses
1 | 3 | 1 - False Alarms
3 | 3 | 1 - Misses
4 | 3 | 1 - False Alarms
1 | 4 | 1 - False Alarms
4 | 4 | 1 - Misses
1 | 1 | 2 - Misses
4 | 1 | 2 - False Alarms
1 | 3 | 2 - False Alarms
3 | 3 | 2 - Misses
4 | 3 | 2 - False Alarms
1 | 4 | 2 - False Alarms
4 | 4 | 2 - Misses
1 | 1 | 3 - Misses
4 | 1 | 3 - False Alarms
2 | 2 | 3 - Misses
1 | 3 | 3 - Hits
4 | 3 | 3 - Hits
1 | 4 | 3 - False Alarms
4 | 4 | 3 - Misses
1 | 1 | 4 - Misses
4 | 1 | 4 - False Alarms
2 | 2 | 4 - Misses
1 | 3 | 4 - False Alarms
3 | 3 | 4 - Misses
4 | 3 | 4 - False Alarms
1 | 4 | 4 - Hits
N

Figure 4.21: Validation output for all 10 cities from validation module of the LCM, TerrSet.

The validation results from ROC statistics which provides AUC value for each LCM model for each city is shown in Table 4.13. All the simulations have a value greater than 0.5 providing satisfactory results.

Table 4.36: Area under curve value for LCM prediction model for each city

Study Areas	AUC
Birmingham and Hoover	0.533
Montgomery	0.703
Mobile	0.606
Huntsville, Madison, and Decatur	0.64
Tuscaloosa	0.584
Dothan	0.683
Auburn	0.707

** AUC is Area Under the ROC curve. Value closer to 1.0 points towards positive predictions*

The results of the simulation indicate that there will be a significant urban built-up expansion in the future. Transportation and physical landform acted as driving forces for urban built-up expansion. Accessibility to main roads, water, settlements, slopes, aspect, and altitude will also act as driving forces for urban built-up expansion in the future. Future growth prediction for urban areas is important to help plan and implement mitigation schemes to reduce impacts of increasing anthropogenic activities in cities. Thus, having knowledge of how the urban areas will look in the next few decades will benefit planning the cities and informing policymakers.

Discussion

As seen from the results, this study has demonstrated the usefulness of satellite remote sensing and digital image processing for LUCC classification. For future growth projection CA-Markov model proved its effectiveness. This study has also examined the evolution of urban spatial form for urban built-up areas in the state of Alabama. Significant growth patterns of urban expansion were found in all 10 cities. As aforementioned in Section “Land Use and Land Cover Change in Results”, the spatial pattern of urban expansion in all the cities are influenced by the presence of transportation routes and water bodies. Birmingham, Montgomery, Dothan, Huntsville, Madison, and Auburn showed significant patterns of growth around transportation routes such as interstate highways and state highways. This expansion can be attributed to economic activities that highways attract and help develop the area along the highway lines. Examples of which are gas stations, hotels, and other service-related businesses. However, access to water bodies seemed to have dominated the growth of urban areas in Mobile, Decatur and Tuscaloosa, by encouraging development around them.

Some of the highlights of the classification of urban areas are:

1. Mainly forest, barren land, and grassland have been urbanized.

2. Most of the urban expansion took place along the interstates. As a result, most of the study areas exhibited linear pattern of urban expansion such as Birmingham, Hoover, and Auburn.

3. Some areas are the results of centrifugal force. For instance, Dothan, Mobile, Huntsville and Montgomery. Some urban areas exhibited dispersed patterns such as Tuscaloosa, Madison, and Decatur.

It was also noted as mentioned in Section “Change Analysis in Results”, the major contributors to urban areas in all the cities are vegetation and barren land. It iterates the fact that natural pervious surfaces are converted to man-made impervious surfaces at exponential rates in

SMSC. This exposes the cities to different disasters making them extremely vulnerable since such cities receive limited funding and limited research. Predicted urban growth also represented the same kind of pattern in the study areas, highlighting growth centering the transportation routes and water bodies. However, it should be noted that the future growth scenario depends on the driver variables selected. Cities development plans and population change are a few of the variables which are not included in this study and should be considered for further studies.

Conclusion

In this paper, we apply random forest algorithm in GEE to classify 4 decades of satellite images for 10 cities of Alabama and used the LCM of TerrSet software to conduct a future change study to 2050 for all the 10 cities. This study has established a well-documented regional case focusing on the state of Alabama. Findings of this study should be utilized in future urban planning strategies, managing resources, and providing direction in a rapidly changing environment. This study has provided the changing form and shape of the cities, past, present, and future which can help guide town planners, road network management and land use.

The 5th Intergovernmental Panel on Climate Change (IPCC) report mentioned that many global risks of climate change are concentrated in urban areas and will be on the rise in future (IPCC, 2014 2014). For example, heat stress, extreme precipitation, flooding, air pollution, drought, and water scarcity pose risks in urban areas for people. Therefore, it is important to understand the impacts, vulnerabilities, and adaptation measures suitable to improve life on Earth. Techniques like CA-Markov future growth model and GIScience are effective tools to aid sustainable planning and development because they can illustrate the foreseeable changes. A well-planned sustainable development strategy can decelerate the negative impacts of modern era urban growth thus highlighting the importance and need of studies like the one presented in this chapter.

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CHAPTER 5: COMMUNICATING SUSTAINABILITY WITH CITIZENS USING OPEN SDG DATA REPORTING PLATFORM: THE GAPS AND CHALLENGES

Introduction

Sustainability can be defined as the ability of a system to continue functioning and providing benefits to its stakeholders' long term, without compromising the well-being of future generations or the natural systems upon which they depend (World Commission on Environment and Development, 1987). Sustainability is often considered as a broad concept that goes beyond just physical changes in the environment. According to the United Nations Development Program (UNDP, 2018), sustainable development involves "meeting the needs of the present without compromising the ability of future generations to meet their own needs". This implies that sustainability requires resources to be used in a manner that allows for meeting present needs while simultaneously conserving the planet's health and ecosystems. Sustainability involves three interdependent dimensions, namely economic, social, and environmental, which necessitate a balance between the aspirations and needs of present and future generations, guaranteeing that economic development does not occur at the expense of social justice or ecological health.

In contrast, resilience denotes the ability of a system to absorb, adjust to, and recover from change and disturbance (Walker et al. 2004). The concept of resilience is often applied in the context of environmental systems, such as ecosystems and landscapes, and refers to their capacity to bounce back from natural or human-induced stressors, such as droughts, fires, or deforestation. However, resilience is also applicable to human systems, such as communities, economies, and infrastructures, and refers to their ability to endure and recover from disruptive events, such as natural disasters, financial crises, or pandemics. Resilience is also a significant aspect of sustainability since resilient communities and systems are more capable of withstanding and recovering from disturbances, stress, and shocks, such as natural disasters, economic downturns, and pandemics. This enhances their ability to tackle future challenges and guarantees their persistence over time (IPCC, 2018).

The relationship between sustainability and resilience is intricate and dynamic, with interdependencies that play important roles. On one hand, sustainability is necessary for resilience, as it provides the essential resources and conditions for systems to endure over time and tolerate change. For instance, a forest ecosystem that is sustainable is more likely to be resilient to fire and pest outbreaks than a degraded or overexploited forest (Holling, 1973). On the other hand, resilience contributes to sustainability by improving the capacity of systems to cope with and adapt to change, reducing the risk of collapse or degradation (Folke et al., 2010). For example, a community that is resilient is more likely to recover from a natural disaster and maintain its social and economic viability than a vulnerable one (Berkes & Ross, 2013).

Despite their interrelatedness, sustainability and resilience are not always compatible, and trade-offs between them may occur. For example, implementing resilience measures such as building seawalls or dams can increase the stability and robustness of a system in the short term, but may also lead to long-term degradation or loss of ecological or cultural values (Gunderson & Holling, 2002). Furthermore, enhancing resilience in one aspect of a system, such as its physical infrastructure, may come at the expense of another aspect, such as its social or ecological diversity, thereby reducing its overall resilience (Holling, 1986).

Consequently, sustainability and resilience are critical concepts in our contemporary world, and their significance cannot be overstated. Sustainability is the ability of a system or community to persist over time, while resilience is the ability to withstand and recover from disturbances, stress, and shocks (Brand and Jax 2007). These concepts help us understand the long-term viability of our ecosystems, economies, and societies. Achieving both sustainability and resilience requires an integrated and holistic approach that considers the multiple and interrelated dimensions of systems, balancing short-term and long-term perspectives. It is essential to recognize that sustainability encompasses social, economic, and cultural factors as well, and is not solely a physical change in the environment (Senge et al., 2004). A sustainable community is one that not only reduces its carbon footprint and conserves its natural resources but also ensures equitable access to opportunities, fosters social cohesion and diversity, and supports cultural heritage and identity (Chapin et al., 2011).

As explained in Chapter 1, the UN has been at the forefront of promoting sustainability and addressing global environmental and social challenges. In 2015, the UN adopted SDGs as part of the 2030 Agenda for Sustainable Development, a comprehensive plan to end poverty, protect the planet, and ensure prosperity for all (United Nations, 2015). The SDGs consist of 17 goals (Figure 1.1), ranging from ending poverty and hunger to promoting gender equality and combating climate change (United Nations, 2015). The SDGs are unique in that they are universal, ambitious, and integrated, reflecting the understanding that sustainable development cannot be achieved in isolation and requires a coordinated effort by all countries and stakeholders (United Nations, 2015). While the SDGs are mostly tailored to countries, they have wide-ranging applications in the world and are being implemented by governments, businesses, civil society organizations, and individuals Governments around the world are using the SDGs as a framework for national development plans, setting targets and monitoring progress (United Nations, 2015; Smith, 2016). According to the UN (2021), over 130 countries have incorporated the SDGs into their national development plans, demonstrating a commitment to sustainable development at the national level. Businesses are also incorporating the SDGs into their strategies and operations, recognizing the role they can play in promoting sustainable development (United Nations Global Compact, 2020; Baumeister & Rauch, 2018). Companies such as Google, Microsoft, and Walmart have set ambitious targets to use renewable energy and reduce their carbon footprint, in line with SDG 7 on affordable and clean energy (Google, 2020; Microsoft, 2021; Walmart, 2021). Additionally, organizations such as Goldman Sachs and Salesforce have launched programs to promote gender equality in the workplace, in line with SDG 5 on gender equality and the empowerment of all women and girls (Goldman Sachs, 2021; Salesforce, 2021).

One notable example of the SDGs in action is the use of renewable energy. The SDG 7 calls for affordable and clean energy for all, and governments, businesses, and communities around the world are taking steps to promote the use of renewable energy sources such as wind, solar, and hydro. (UN, 2015) For example, countries such as Costa Rica, Iceland, and Sweden have set ambitious targets to transition to 100% renewable energy, (Renewable Energy Policy Network for the 21st Century, 2017) while businesses such as Google, Microsoft, and Walmart have set similar targets for their operations. (Baumeister & Rauch, 2018). Another example of the SDGs in action is the promotion of gender equality. SDG 5 calls for gender equality and the empowerment of all women and girls, and organizations and governments around the world are taking steps to promote gender equality and address gender-based violence and discrimination. (UN, 2015). For example, the UN Women initiative provides support to governments and civil society organizations in implementing the sustainable development.

Civil society organizations are working to raise awareness of the SDGs and mobilize action. For example, the UN Women initiative provides support to governments and civil society organizations in implementing the SDGs (UN Women, 2021). Meanwhile, individuals are taking action in their own communities to contribute to the SDGs, for example, through volunteering, reducing their own carbon footprint, and supporting sustainable development projects (United Nations, 2015).

In summary, the United Nations has been instrumental in promoting sustainability and addressing global environmental and social challenges through initiatives such as the SDGs. The SDGs provide a comprehensive framework for sustainable development that is being implemented by governments, businesses, civil society organizations, and individuals around the world, with a focus on ending poverty, protecting the planet, and ensuring prosperity for all.

Cities as important drivers for sustainability and resilience

Cities are important drivers of sustainability, as they are home to the majority of the world's population and contribute significantly to global greenhouse gas emissions. As stated in Chapter 1, over 50% of the global population lives in urban areas, and this trend is expected to continue, even in underdeveloped and impoverished areas such as the cities in Alabama, as highlighted in Chapter 4. Goal 11 of the UN SDGs aims to ensure sustainable cities and communities. This goal seeks to make cities and human settlements inclusive, safe, resilient, and sustainable. SMSC particularly plays a vital role in promoting sustainability, as they comprise the majority of cities globally and are often the centers of economic, cultural, and political activity in their respective regions (UN, 2018). SMSC have an advantage in achieving this goal because they are more manageable in terms of size and more adaptable to change. They can more easily implement sustainable solutions, such as renewable energy systems, green spaces, and sustainable transportation, than larger cities. This is because smaller cities have a more compact urban form and a stronger sense of community, which can facilitate the implementation of sustainable solutions.

Furthermore, Goal 7 of the UN SDGs aims to ensure access to affordable, reliable, sustainable, and modern energy for all. SMSC have the potential to lead the way in the transition to renewable energy, as they have less complex energy systems and more opportunities to experiment with new technologies. SMSC can reduce their dependence on fossil fuels, thereby reducing greenhouse gas emissions and improving energy security (UN, 2018). This can be achieved through a variety of means, including the installation of rooftop solar panels, the development of community-scale wind farms, and the implementation of energy-efficient building codes and technologies (UN, 2018). In addition to energy, SMSC can also contribute to sustainable water management (Goal 6). According to the United Nations, nearly 2 billion people lack access to safe drinking water, and this problem is particularly acute in urban areas. SMSC can address this issue by implementing sustainable water management systems, such as rainwater harvesting and greywater reuse. This can help to reduce the demand for treated water and improve water security for all citizens. SMSC also plays a crucial role in promoting sustainable transportation (Goal 11). According to the World Health Organization, air pollution is responsible for 7 million premature deaths each year, and this problem is particularly acute in cities (World Health Organization 2023). SMSC can address this issue by promoting sustainable transportation, such as cycling, walking, and public transportation. This can help to reduce emissions, improve air quality, and promote active and healthy lifestyles for all citizens. By reducing dependence on single-occupancy vehicles, SMSC can reduce greenhouse gas emissions and improve air quality, while also improving access to transportation for all residents (UN, 2018). Additionally, SMSC can contribute to sustainable waste management (Goal 12). According to the United Nations, the world generates approximately 1.3 billion tons of solid waste each year, and this figure is expected to increase to 2.2 billion tons by 2025. SMSC can address this issue by implementing sustainable waste management systems, such as composting and recycling. This can help to reduce waste, improve resource efficiency, and conserve natural resources for future generations.

In conclusion, SMSC plays a crucial role in promoting sustainability and achieving the UN SDGs. They have an advantage in terms of size and adaptability, which makes them more suited to the implementation of sustainable solutions. By focusing on achieving such goals in SMSC, they can contribute to a more sustainable future for all.

Urban Integrated services and citizen engagement

One of the ways to achieve smooth functioning of any city in a sustainable manner is implementing UIS. UIS are complex networks of interconnected infrastructure and services, such as transportation, energy, water, and waste management, that support the functioning of cities. Effective management and operation of UIS requires significant collaboration and coordination between various stakeholders, including government agencies, private companies, and citizens and effective and efficient data management and analysis (Grimmond et al. 2018).

Citizen engagement refers to the involvement of the public in the decision-making process of urban development in this context. It is important because it helps to create a more democratic, accountable, and transparent system. By engaging with citizens, urban planners can understand their needs and priorities, which can inform the design and implementation of integrated systems. For example, in chapter 2, a survey conducted among residents of a city can reveal the most pressing transportation issues, such as congestion, lack of accessibility, and safety concerns. This information can be used to develop and implement transportation systems that better serve the needs of the community. Citizen engagement also helps to build trust and legitimacy in the decision-making process. When citizens feel that their voice is heard and their needs are being addressed, they are more likely to support and participate in the implementation of UIS. This can lead to increased collaboration between government and citizens, resulting in more effective and efficient systems as explained in Chapter 2 and 3. In addition to providing valuable input during the planning phase, citizens can also play an active role in the ongoing operation and management of UIS. For example, they can provide real-time data on traffic patterns and energy consumption, which can be used to optimize the functioning of these systems. In addition, they can also help to monitor and maintain these systems and report any issues or problems that need to be addressed.

Data management for sustainable solutions

Data management is another critical aspect of UIS. Accurate and up-to-date data is essential for informed decision-making, monitoring, and evaluation of these systems. Effective data management requires a robust infrastructure and clear processes for data collection, storage, and analysis. This involves the use of sensors, data platforms, and analytical tools to collect and manage data. It also requires collaboration between different departments and agencies to ensure that data is being used effectively. Data is an essential component in understanding patterns and generating visualizations that can convey information to the public. Many studies have examined the potential of using data in urban planning, resilience, and sustainability as explained in the Introduction chapter.

Data communication

Effective data reporting is essential for monitoring progress towards the SDGs and making informed decisions to support sustainable development. It requires collaboration between government agencies, NGOs, private sector organizations, and other stakeholders. The use of web-based technologies, such as websites and online platforms, has revolutionized the way data is shared and accessed, enabling large amounts of data to be collected, processed, and disseminated in real-time. This increased accessibility has led to greater transparency and accountability, as well as increased participation in decision-making processes (UN 2021). Open data, which refers to data that is freely available for anyone to use without restrictions, has also been identified as a key aspect of effective data reporting. The use of open data allows for a wider range of stakeholders to access and use data, leading to better outcomes for sustainable development (Open Data Institute 2021).

Web-based technologies also provide new opportunities for real-time data collection and analysis, which can inform more dynamic approaches to sustainable development. For example, the UN Global Platform for Disaster Risk Reduction allows governments, organizations, and individuals to share data on natural disasters and their impacts, helping to build a more comprehensive understanding of the risks and consequences of these events. This data can then be used to inform disaster risk reduction strategies, helping to mitigate the impacts of future disasters and support sustainable development (UN 2021). In addition, the use of the internet and web-based technologies facilitates collaboration and coordination between different stakeholders.

Citizen engagement, effective data management, and data communication are not only important to create sustainable urban integrated systems but also to improve overall quality of life by tackling and addressing social aspects of sustainability. Numerous levels of research have justified the importance of involving stakeholders and practitioners in coming up with solutions for various sustainability challenges. But is it feasible to implement the SDGs at all spatial levels and how? Do they involve citizens in making decisions or imposed on them? Keeping these questions in mind, this research, probably the first of its kind, explores the creation, validation, and usage of survey instruments to understand the awareness/familiarity, concern/urgency, perception, involvement, behavior, and intended behavior of SEUS citizens (via survey) about sustainability practices based in UN SDGs in Chapter 2 and 3, and uses the result of this survey for the creation of a data reporting platform for a small city, Auburn, in SEUS which is growing fast in this chapter. The data reporting platform is based on the UN open SDG data reporting platform ("Home - Open SDG" 2023) and is a central place to view, understand, and collect information about the goals of any area. The aim is to assess the feasibility of implementing the SDGs at the local level, and to identify key areas for improvement in data management, reporting, and sustainability efforts required by SMSC to attain these goals by 2030. The ultimate objective is to create an effective UIS that promotes sustainability in SMSC.

Study area

Auburn (Figure 5.1) is a mid-size, vibrant, and historic city in the state of Alabama. It is located in the east-central part of Alabama. It is best known as the home of Auburn University, one of the largest and most prestigious universities in the Southeast, which is also Auburn's main source of employment for the residents. The university adds to the cultural and educational fabric of the city and its students bring a youthful energy to the community. Additionally, the city being a university town has a transitory inflow and outflow of students. Because the majority of individuals rent their apartments, most housing is designed to meet their needs. The city has an estimated population of 63,793 and ranks as Alabama's eighth largest city (US Census 2020). It was also ranked as the fastest growing city in the state of Alabama by the U.S Census Bureau in

2016 (US Census 2016). The urban built-up area of the city has increased from approximately 1.42% in 1990 to 5.38% in 2020, with a net addition of over 199%, as analyzed in Chapter 4. According to estimates, the urban area of Auburn is expected to increase from 2,056 ha in 2010 to 6,293 ha by 2050 (Chapter 4).

The city is a vibrant center of commerce, industry, and education, offering residents a high quality of life, including a low cost of living, excellent schools, and a strong sense of community. This variable population size requires the city to be better prepared to cater to the changing environmental and spatial nuances.

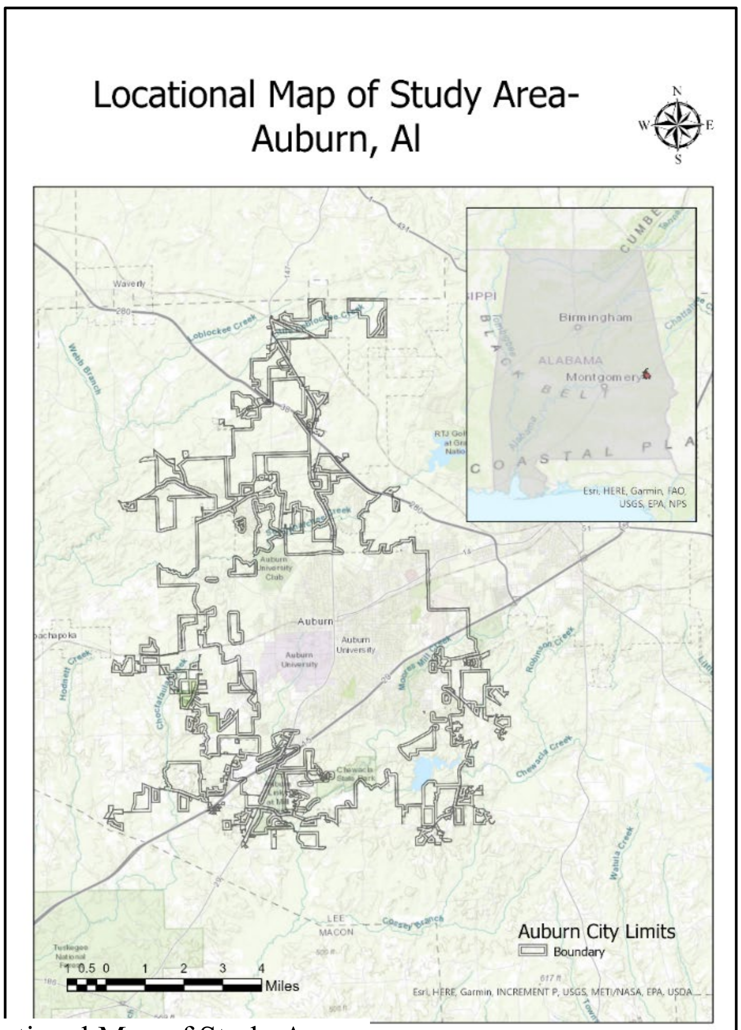


Figure 5.22: Locational Map of Study Area

Methods

Data Collection

The data reporting platform is based on the survey created in Chapter 2. Seven out of seventeen UN SDGs were chosen as a basis for this research by the Auburn-Opelika residents. The seven SDGs chosen are:

Goal 1: No Poverty

Goal 2: Zero Hunger

Goal 3: Good Health and Well-being

Goal 4: Quality Education

Goal 6: Clean Water and Sanitation

Goal 7: Affordable and Clean Energy

Goal 8: Decent Work and Economic Growth

The UN SDGs reporting framework consists of three components: goals, targets, and indicators which provide a comprehensive and integrated framework for sustainable development at the global, regional, and national levels. The 17 SDGs, along with a total of 169 targets and 248 indicators, that would address key sustainable development challenges and promote sustainable development for all (UN, 2015) were developed through a participatory and consultative process involving stakeholders from around the world, including governments, civil society organizations, the private sector, and academia (UN, 2017). Under each goal, there are a set of targets that provide a more specific focus for action, and under each target, there are one or more indicators that measure progress towards achieving that target (United Nations, n.d.). Each indicator is carefully selected based on its relevance, feasibility, and measurability, and is designed to be globally applicable while also considering local context (United Nations, 2018).

As SDGs are used as a framework to collect and inform data related to sustainability achievement in this research, abovementioned seven selected goals' targets and indicator information are used to report a comprehensive and integrated information at city level. For this research, we had a total of 63 targets, and 99 indicators among the 7 goals. Due to the nature of the goals, targets, and indicators being used for global, regional, and national levels some of the information was not applicable and some were not reported at city level. The indicators reported were also reported at different temporal scales which is reflected in the data reporting platform created. Such indicators are either modified or reported as not applicable for Auburn, Al.

University databases, federal databases, ESRI geographic databases, city websites, community profile, and general internet search were used to collect such data. This data was then used to assess the feasibility of implementing SDGs at a city level in the SEUS. Certain GIS layers were also created to show the demographic information of the city. ESRI enrich datasets were used for this purpose.

Data sources

The following are the data sources used to collect information about the different indicators used in this study:

US Census

The United States Census is a census that is conducted every ten years by the U.S. Census Bureau, a part of the U.S. Department of Commerce. The census is conducted to gather information about the population of the country, including demographic information such as age, race, and ethnicity, as well as economic information such as employment and income. This information is used by the federal government to make decisions about how to allocate resources and distribute funds for various programs.

The 2022 United States Census was the 24th decennial census, conducted by the U.S. Census Bureau from April to August of that year. The census aimed to count every resident in the United States, including citizens and non-citizens, and gather important demographic information about the population. This information is used by the federal government to allocate resources and funding for various programs, as well as to determine the number of seats each state has in the U.S. House of Representatives. The census faced a number of challenges in 2022, including the ongoing COVID-19 pandemic and a shortened timeline for completion. Despite these challenges, the U.S. Census Bureau was able to successfully gather data from millions of households across the country. The data collected in the 2022 census will provide a snapshot of the demographic and economic characteristics of the country and will be used to inform decisions about resource allocation and program funding for years to come. This study utilizes census information especially from 2022 census.

American Community Survey (ACS)

ACS is a yearly survey conducted by the U.S. Census Bureau to gather information about the demographics, housing, and economic characteristics of the U.S. population. It is an important tool for communities and policymakers, as it provides detailed information about the population and its characteristics that can be used to inform decisions about resource allocation and program funding. The data collected by the ACS is used by a wide range of organizations and agencies, including state and local governments, non-profit organizations, and private businesses. The ACS is also a valuable resource for researchers, as it provides a comprehensive picture of the U.S. population and its characteristics over time.

There are several different types of data that are collected and stored in the ACS database, including:

1. Demographic Data: This includes information about the age, race, ethnicity, and gender of the population, as well as data on immigration and citizenship status.
2. Housing Data: This includes information about the type of housing units, the number of rooms, the age of the structure, and the occupancy status of housing units.
3. Economic Data: This includes information about employment, income, poverty, and health insurance coverage.
4. Education Data: This includes data on educational attainment, enrollment in school, and degrees earned.
5. Mobility Data: This includes information about migration patterns and the mobility of the population.
6. Disability Data: This includes data on the prevalence of disabilities among the population and the type of disability.
7. Language Data: This includes information about the languages spoken by the population and the prevalence of non-English speaking households.
8. Commuting Data: This includes information about the mode of transportation used by individuals to commute to work.

The data collected in the ACS database is available at various levels of geography, including the national level, the state level, and the local level. ACS also provides year estimates of data for various geographic levels, including the national level, state level, and local level. These year estimates are available for different time periods, including:

1. One-Year Estimates: These estimates are based on data collected from a sample of the population over a one-year period, and provide detailed information about

the demographics, housing, and economic characteristics of the population.

2. Three-Year Estimates: These estimates are based on data collected from a sample of the population over a three-year period and provide a more reliable picture of the population than one-year estimates, but with less detail.
3. Five-Year Estimates: These estimates are based on data collected from a sample of the population over a five-year period and provide an even more reliable picture of the population than three-year estimates, but with even less detail.

Each year's estimate has its own advantages and disadvantages, depending on the level of detail and reliability needed for a particular use case. For example, if a user wants to examine the demographics of a small geographic area, they may prefer to use the one-year estimate, as it provides the most detail. On the other hand, if a user wants to examine the characteristics of a larger geographic area, they may prefer to use the five-year estimate, as it provides the most reliable picture of the population. For this research, One-Year estimates and Five-Year estimate information was widely used to collect information for Goal 1 and Goal 3.

City data

City-Data.com is a website that provides information about cities and neighborhoods in the United States. The site offers a wide range of data, including demographic information, crime rates, housing prices, and more. The information is intended to help people make informed decisions about where to live, work, and visit. Additionally, the site also includes forums where people can discuss various topics related to their communities. This website is privately owned and collects data from various sources. It is widely used for this research, as it provides information at city level.

Auburn City School

Auburn City Schools is a school district in Auburn, Alabama that serves the city's public-school students. Information about the district and its schools can typically be found on the district's website or on websites like GreatSchools.org or Niche.com, which provide data and ratings of individual schools. Auburn city school also had their own website where data such as enrollment figures, student-teacher ratios, test scores, graduation rates, and more were collected especially for Goal 4.

CDC health database – Alabama public health

The Centers for Disease Control and Prevention (CDC) provides a wealth of information on public health topics, including data on various health conditions, outbreaks, and health disparities. In Alabama, the CDC works in partnership with the Alabama Department of Public Health to collect, analyze, and disseminate public health data.

Some of the data that could be found on the CDC website for Alabama includes information on infectious diseases, such as outbreaks of foodborne illness and sexually transmitted infections, as well as data on chronic diseases, such as diabetes, heart disease, and cancer. The website also provides data on behavioral health, including information on substance abuse and mental health. They also provide data on deaths including maternal and infant mortality rates at different spatial scales. CDC website was specifically used for Goal 3.

DataUSA.io

DataUSA is a website that provides a wealth of data and information on the United States, including information on demographics, employment, education, and more. The site offers data at the national, state, and metropolitan area levels, and provides interactive visualizations and tools to help users explore and understand the data. Some of the data available on DataUSA includes information on population demographics, labor force participation, median household income, and more. The site also provides data on specific industries, including information on employment, wages, and productivity.

DataUSA aims to make it easy for anyone to access, understand, and use data to inform decisions and drive action. The site is updated regularly with the latest data, and provides information from a variety of sources, including the U.S. Census Bureau, Bureau of Labor Statistics, and more. This website was used in some capacity to collect information for indicators for all 7 goals.

Auburn City website

The official website of the City of Auburn, Alabama is https://www.auburnalabama.org/. This website provides information on a variety of topics related to the city, including government services, events, and community resources. Some of the information you can find on the website includes:

1. Information on city departments and services, including police, fire, and public works.
2. A calendar of events and activities taking place in Auburn
3. Information on city parks and recreational opportunities
4. Resources for businesses, including information on business licenses and permits.
5. Information on city utilities, including water and sewer services.

The website also provides a range of resources for residents, including information on waste and recycling services, and information on community programs and services. This website was used overall to gather information on all 7 goals.

USA.com

USA.com is a website that provides information on various aspects of life in the United

States, including data on demographics, geography, and more. The site offers information on individual states, cities, and counties, including data on population, housing, and more. In addition to data, USA.com also provides information on businesses, schools, and other organizations in the United States. Some of the information available on the site includes contact information, maps, and reviews of businesses, schools, and other organizations. This website was mostly used for collecting indicator information of Goal 3 and 7 at state level.

World population review

World Population Review (www.worldpopulationreview.com) is a website that provides information and data on various aspects of world demographics, including population size, growth, and distribution. The site provides data on population by country, including information on population density, urbanization, and more. Some of the information that could be found on the World Population Review website includes:

1. Data on population by country, including the total population and population growth rate.
2. Information on population density and urbanization, including the percentage of the population living in urban areas.
3. Data on age structure and life expectancy, including information on the median age and average life expectancy of the population.
4. Information on birth and death rates, including the crude birth rate and crude death rate.
5. Data on immigration and emigration, including information on the number of people entering and leaving a country.

The World Population Review aims to provide a comprehensive resource for information on world demographics, and the site is updated regularly with the latest data. It was mostly used to report modified indicators for Goal 3.

Energy Information Administration (EIA)

The EIA is a statistical agency within the U.S. Department of Energy. The EIA is responsible for collecting, analyzing, and disseminating independent and impartial energy information to promote sound policymaking, efficient markets, and public understanding of energy and its interaction with the economy and the environment. The EIA's website, www.eia.gov, provides access to a wide range of energy data and analysis, including information on production, consumption, prices, and imports/exports of various energy sources, such as petroleum, natural gas, coal, nuclear energy, and renewable energy. In addition to data and analysis, the website also provides insights and analysis on energy market trends, energy policy and legislation, and energy technology. The EIA's website is a valuable resource for anyone looking for information and insights on energy and energy-related topics in the United States.

Some of the data and information you can find on the EIA's website include:

1. Energy data, including production, consumption, prices, and imports/exports of various energy sources, such as petroleum, natural gas, coal, and renewable energy.
2. Analysis of energy markets and trends, including projections of future energy use and prices.
3. Data on electric power, including information on electricity generation, transmission, and consumption.
4. Information on energy-related carbon dioxide emissions, including data on emissions by energy source and sector.

5. Data on energy efficiency, including information on energy use in buildings, transportation, and industry.

The EIA's website also provides a range of tools and resources, including interactive data visualizations, analysis and reports, and an online data browser that allows users to access and download energy data. Despite EIA’s plethora of data and easy accessibility most of the data about energy was not reported at city level so this was used to record information of indicators of goal 7 at the state level.

Enrich Layer

Enrich Layer is an analysis geoprocessing tool provided by Esri that allows users to add demographic, economic, landscape, and community data to their geographic data layers. The tool is designed to help users gain insights and make informed decisions by providing a more comprehensive view of their data. One example of its use is in emergency management and disaster response, where Enrich Layer can be used to add data on population density, infrastructure, and vulnerability to natural hazards to existing maps and data layers. This can help emergency managers better understand the potential impact of a disaster and plan response efforts accordingly. In a study on flood risk assessment, Enrich Layer was used to add data on population density, land use, and impervious surfaces to a flood inundation map, allowing for a more accurate assessment of flood risk (Xie et al., 2018). The Enrich Layer tool is also used in sustainability research, where it can be used to add data on energy consumption, emissions, and water use to spatial data layers, helping researchers understand the environmental impacts of different areas and make more informed decisions about sustainable development (Li et al., 2020). For this study, enrich layer was used to create geospatial visualization of different demographic, economic, landscape, and community information for Auburn, AL.

Data reporting platform

The Open SDG Data Reporting Platform is an open-source solution for tracking progress towards the Sustainable Development Goals (SDGs). It provides a standardized way for governments, organizations, and individuals to report on their efforts to achieve the 17 SDGs and their associated targets and indicators. The platform is designed to be flexible and customizable, allowing users to add their own data sources, create custom dashboards and visualizations, and incorporate additional SDG data and view other SDG information as well.

The creation of the Open SDG Data Reporting Platform is a collaboration between OpenAI, the United Nations Development Programme, and other organizations. The platform is based on open data standards, including the SDG Indicator Registry and the SDG Data Hub. It also uses cutting-edge technologies such as machine learning and natural language processing to analyze and present the data in a user-friendly and accessible way. The development and implementation of the Open SDG Data Reporting Platform involves several key stages, including staging, testing, and deployment. Each of these stages plays an important role in ensuring that the platform is built and deployed in a safe, secure, and effective manner.

The staging stage involves setting up a separate environment for testing and refining the platform's code and functionality. This stage is crucial for catching and fixing any bugs or issues that may impact the platform's performance or usability. The staging environment should be set up to closely resemble the final production environment, so that developers can test the platform under realistic conditions. During this stage, developers will also preview the platform's website and test its features, including data input, visualization, and collaboration tools. The testing stage involves conducting thorough testing of the platform's functionality to identify and fix any remaining issues. This stage may involve a range of tests, from simple manual tests to complex automated tests, and may also involve user testing to ensure that the platform is accessible, user-friendly, and meets the needs of its users. The deployment stage involves releasing the platform to its users and making it available to the public. During this stage, the platform is installed and configured in the production environment, and the code and data are transferred from the staging environment to the production environment. The platform is then monitored and maintained to ensure that it continues to function as expected and to address any issues that arise.

In the staging stage of the Open SDG Data Reporting Platform, several tools and technologies may be used to manage the codebase and development process. One of the key tools is GitHub, a web-based platform for version control and collaboration. GitHub allows multiple developers to work on the platform code simultaneously, making it easier to manage changes and keep track of the development process. Another tool that may be used during the staging stage is GitHub Pages, a feature of GitHub that enables users to host simple websites directly from their GitHub repositories. Additionally, Jekyll, a popular static site generator, can be used in combination with GitHub Pages to create and manage the platform's website.

The development of the platform may also require the use of programming languages such as Ruby and Python. Ruby, for example, is commonly used for server-side scripting and for building custom plugins and extensions for the platform. Python, on the other hand, may be used for data analysis and processing, as well as for building machine learning models to improve the platform's functionality. To deploy the Open SDG Data Reporting Platform, there are several dependencies and requirements that must be met, example PHP extensions, including OpenSSL, MBString, and XML, Apache, and SSL certificate.

This study solely encompasses the staging and testing stages as the developmental phase necessitates the involvement of organizational stakeholders. The staging stage is publicly accessible through GitHub Pages, enabling individuals to access and comprehend the available data to the public and the city's progress concerning sustainable development.

Results

Upon examining the datasets outlined above, the open SDG data reporting platform was established. Figure 5.2 demonstrates that out of the 99 indicators spanning 7 goals, 41 could be reported while 58 were deemed irrelevant. Each goal has its own individual page which shows the indicators reported online or indicated as not applicable (example: Figure 5.3). Furthermore, each indicator has its own page which includes visualization of data reported in the form of bar or line charts, tables, and information of its metadata (example: Figure 5.4). In terms of goal 1, the majority of indicators were reported at the city level, whereas most of the other goals necessitated modifications to facilitate reporting at either the county or state level. Regarding goal 2, only 3 indicators could be reported, requiring modification to report at the county level or for the entire population of Auburn instead of being divided by demographic groups. Goal 3 comprised 14 reported indicators, which had to be modified for reporting at the county and state level as no indicator information could be found at the city level. In relation to goal 4, which pertains to quality education, Auburn city schools were an excellent source for reporting indicator information. However, all indicators needed to be modified to some degree to report the available information, which differed from the standard provided by the UN. The indicators associated with goal 6, which concerns the sustainable management of water, proved to be the most difficult to report as Auburn city reports information that is entirely distinct from what the UN expects to be reported. As a result, only 3 out of 11 indicators could be reported with modifications. Goal 7, which relates to sustainable and modern energy accessibility, was also challenging to assess, with only 2 indicators reported with modifications as most questions focused on renewable and clean energy, which are primarily reported at the state or country level. Finally, most of the indicators addressing goal 8, which targets sustained, inclusive, and sustainable economic growth, were reported at the city level, with two modified and 9 deemed irrelevant. These findings demonstrate that while the UN SDGs can serve as an excellent standard to follow, they must be adapted to specific contexts, such as cities, as different regions, countries, and cities report information at varying spatial, temporal, and cultural scales.

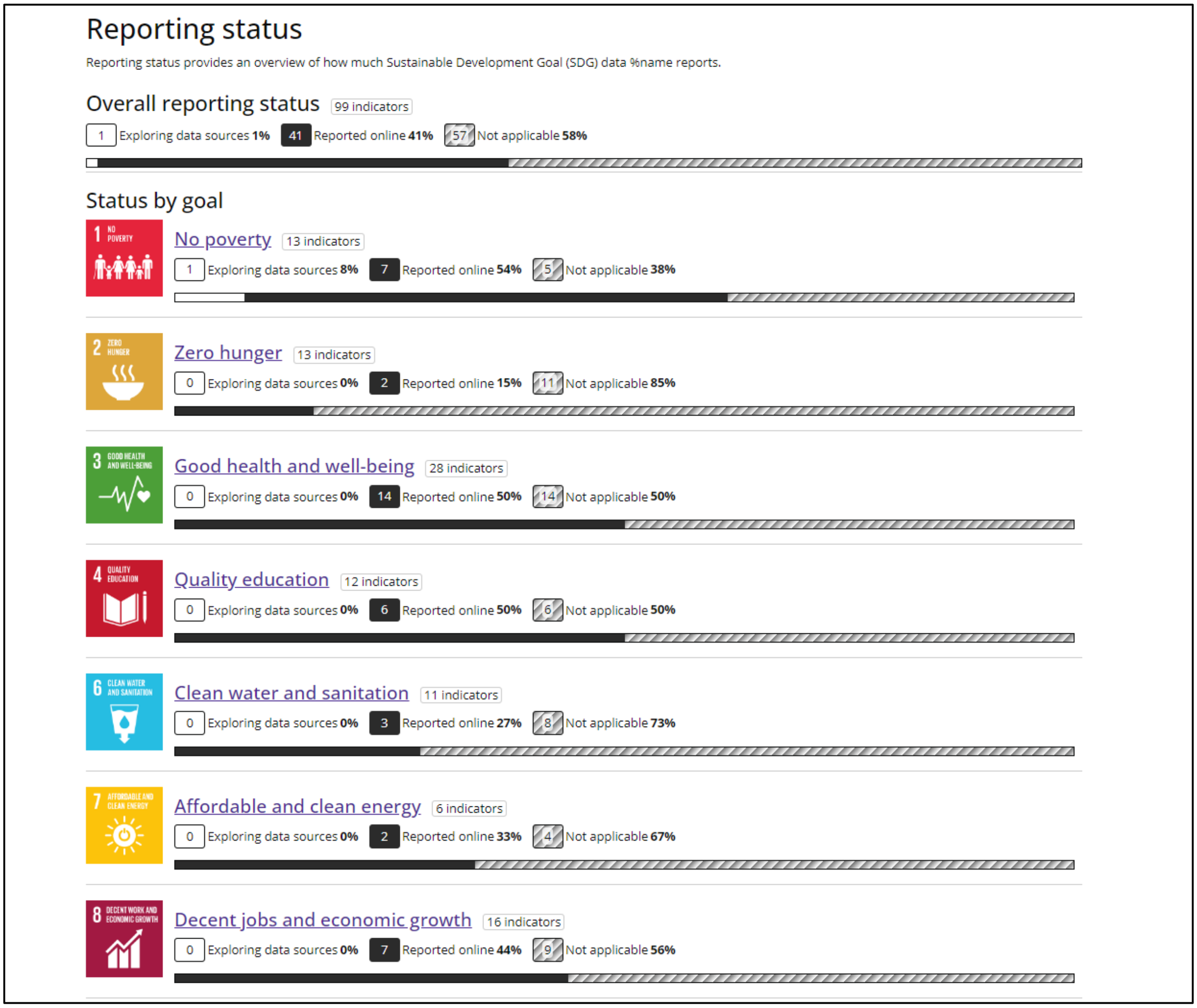


Figure 5.23: Reporting status of 7 SDG indicators as seen on the website.

Goal 1

Goal 1, titled "End Poverty in all its forms everywhere," includes indicators that mainly deal with demographic information (refer to Figure 5.3). As shown in Figure 5.4, the indicator 1.1.1 page displays the data in both chart (bar) and table format, including its metadata. To obtain this data, the US census and ACS databases were utilized. Seven indicators were reported and six were identified as not applicable. The data reported were tailored to fit the context of the US. Indicators 1.1.1 and 1.2.1 were modified to reflect the poverty standard, as $1.25 per day is considered exceptionally low for US citizens. Similarly, indicators 1.4.1 and 1.4.2 were modified to report information on basic services and occupancy based on the data reported by the city. Lastly, indicators 1.5.1 and 1.5.2, which focus on building resiliency for the poor, were adjusted to report at the state level, since this information was not readily available at the city level.

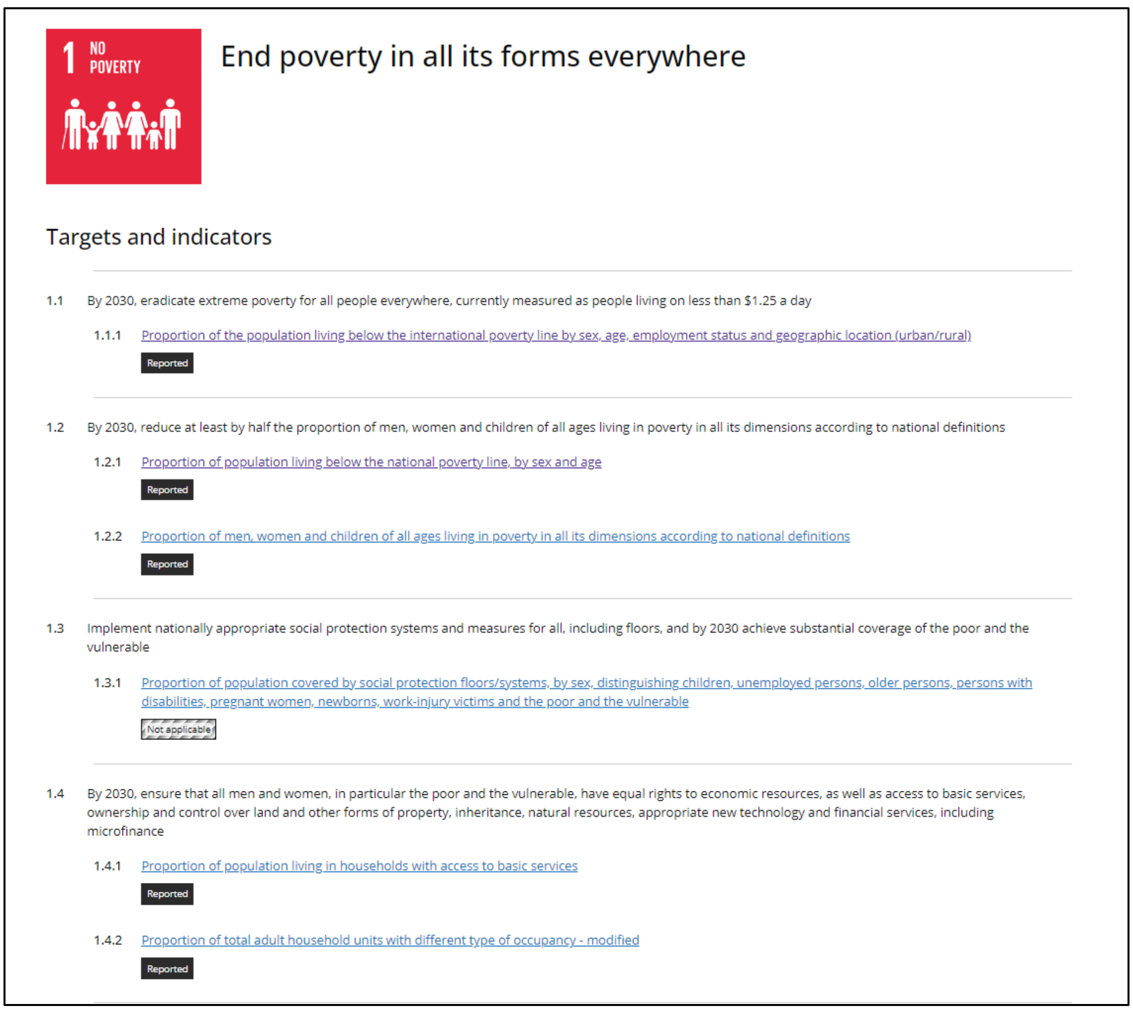


Figure 5.24: Goal 1 homepage

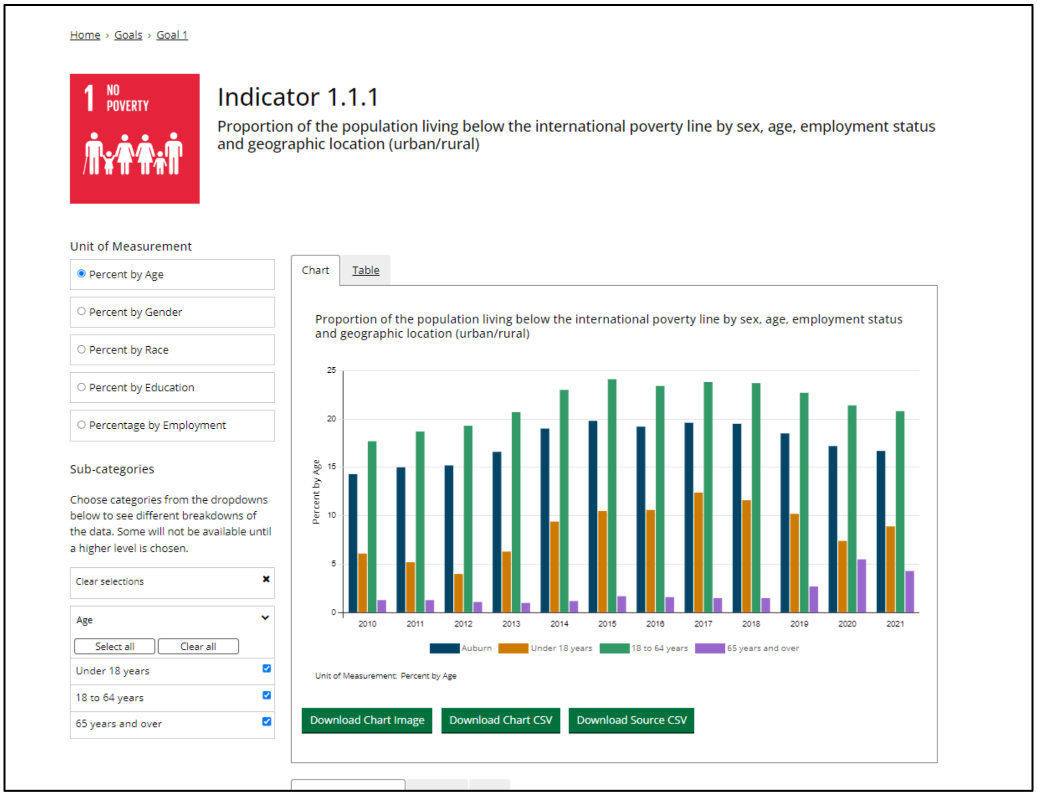


Figure 5.25: Indicator 1.1.1 page

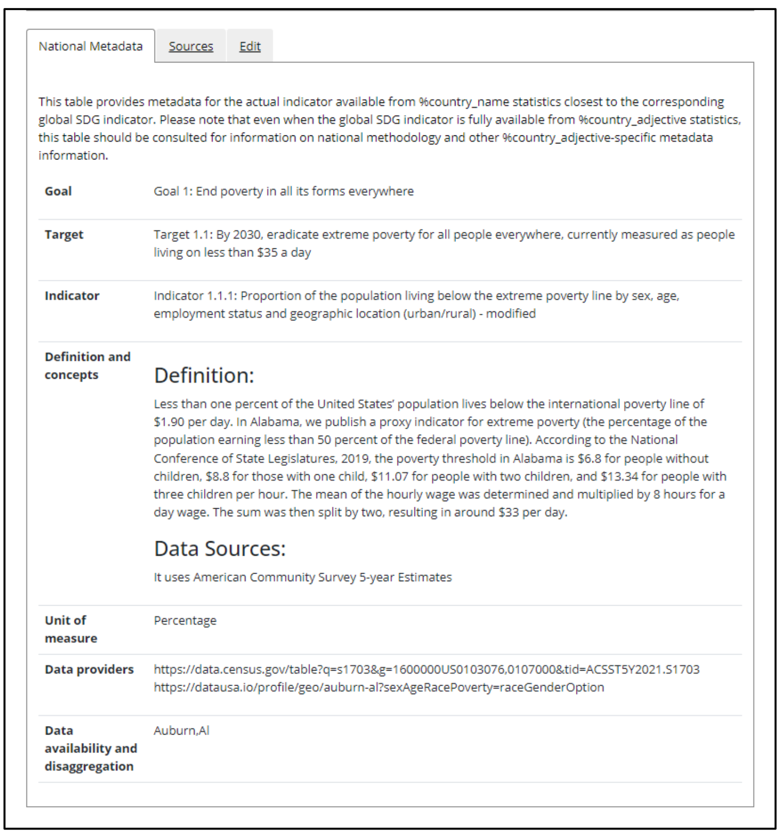
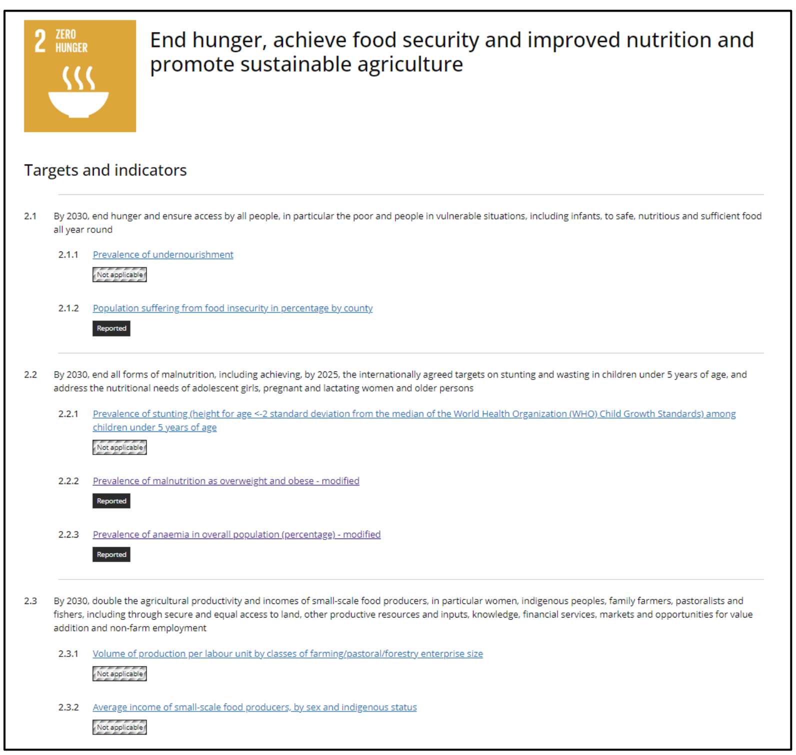


Figure 5.26: Indicator 1.1.1 information page

Goal 2

Goal 2, titled "End hunger, achieve food security and improved nutrition and promote sustainable agriculture," comprises indicators that were primarily obtained from the City-Data website (Figure 5.6). Figure 5.7 illustrates the 2.1.1 indicator page, which provides visualizations of data in chart (line) and table formats, along with its metadata. Due to the limited availability of information regarding food security and nutrition at the city level, the City-Data website was utilized, albeit being privately owned and operated, potentially rendering some of its data questionable. Of the total indicators, only 3 were reported, and 11 were deemed not applicable. Furthermore, the reported data was adjusted either to the county level or the population level, without any demographic distinctions. Indicator 2.1.2 was reported at the county level, while the indicators 2.2.2 and 2.2.3 were modified to denote malnutrition as overweight and obese and anemia, respectively, for the entire population, rather than solely in children and pregnant



females in accordance with the United Nations standards.

Figure 5.27: Goal 2 homepage

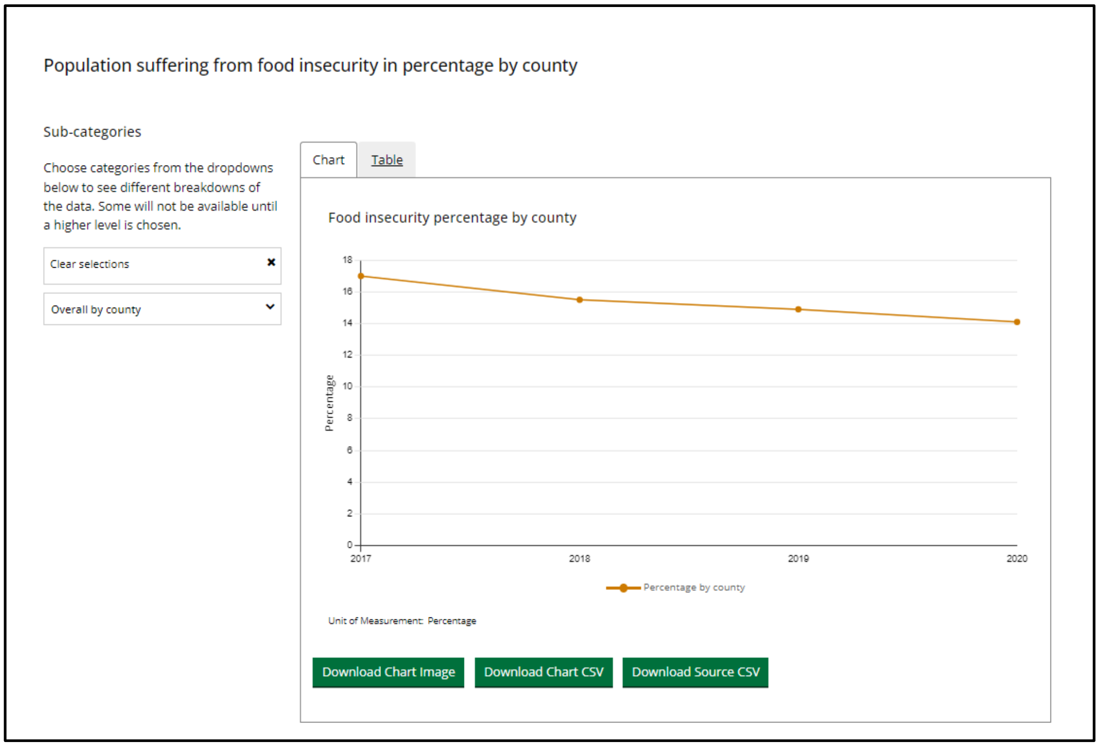
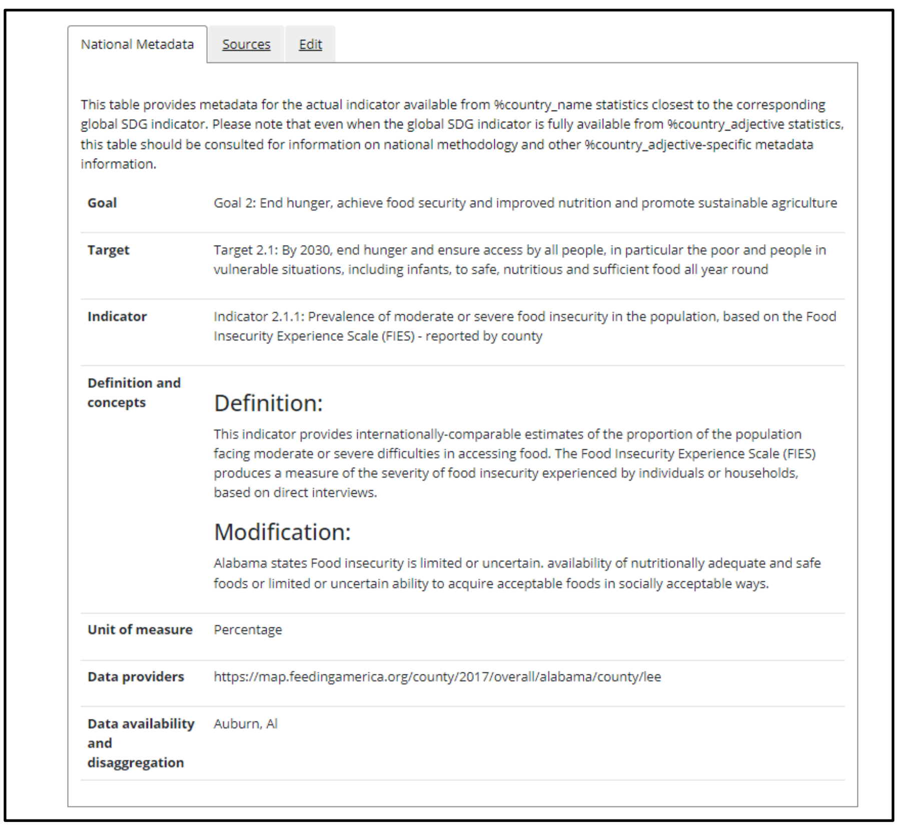


Figure 5.28: Indicator 2.1.2 page


National Metadata | Sources | Edit

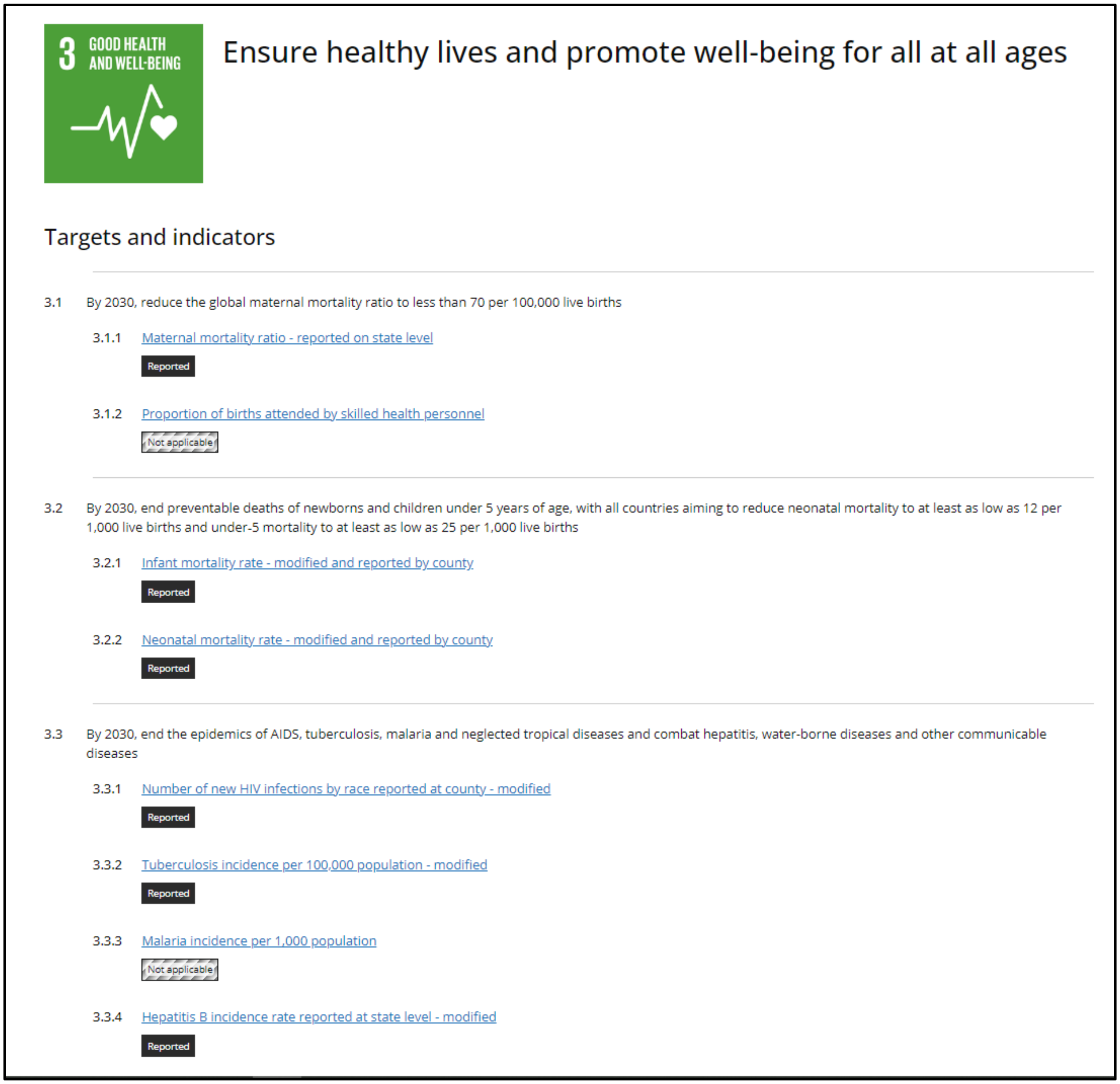
This table provides metadata for the actual indicator available from %country_name statistics closest to the corresponding global SDG indicator. Please note that even when the global SDG indicator is fully available from %country_adjective statistics, this table should be consulted for information on national methodology and other %country_adjective-specific metadata information.

Goal	Goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture
Target	Target 2.1: By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round
Indicator	Indicator 2.1.1: Prevalence of moderate or severe food insecurity in the population, based on the Food Insecurity Experience Scale (FIES) - reported by county
Definition and concepts	**Definition:** This indicator provides internationally-comparable estimates of the proportion of the population facing moderate or severe difficulties in accessing food. The Food Insecurity Experience Scale (FIES) produces a measure of the severity of food insecurity experienced by individuals or households, based on direct interviews. **Modification:** Alabama states Food insecurity is limited or uncertain. availability of nutritionally adequate and safe foods or limited or uncertain ability to acquire acceptable foods in socially acceptable ways.
Unit of measure	Percentage
Data providers	https://map.feedingamerica.org/county/2017/overall/alabama/county/lee
Data availability and disaggregation	Auburn, Al

Figure 5.29: Indicator 2.1.2 information page

Goal 3

Goal 3 titled "Ensure healthy lives and promote well-being for all at all ages" was almost entirely modified to report at the county and state level (Figure 5.9). Only 2 health-related information, i.e., road accidents and health coverage, were reported at the city level. The decision to modify and report the data at the county and state level was necessary due to the lack of health-related information at the city level. This could be due to the absence of a large hospital in the city, with the nearest one being in Auburn and Opelika. The Centers for Disease Control and Prevention (CDC) health data and USA.com were used to report the indicator information for this goal. The visualization of the data in chart (bar) and table format, including its metadata, for the indicator 3.2.1 is shown in Figure 5.10. A total of 14 indicators were reported, while 14 were deemed not applicable. Information about alcohol consumption, vaccines, and tobacco usage among high school students were reported from USA.com, whereas mortality rates were reported from the CDC website. These datasets were also reported at different temporal scales as each health indicator is reported at different time intervals. Indicators 3.1.1, 3.3.4, 3.5.2, 3.a.1, and 3.b.1 were reported at the state level, while indicators 3.2.1, 3.2.2, 3.3.1, 3.3.2, 3.4.1, 3.4.2, and 3.7.2 were modified to report at the county level. Some indicators, such as indicators 3.3.3 and 3.3.5, were more suited to tropical areas, making them not applicable for Auburn, AL.



3 GOOD HEALTH AND WELL-BEING

Ensure healthy lives and promote well-being for all at all ages

Targets and indicators

3.1 By 2030, reduce the global maternal mortality ratio to less than 70 per 100,000 live births

3.1.1 Maternal mortality ratio - reported on state level

Reported

3.1.2 Proportion of births attended by skilled health personnel

Not applicable

3.2 By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births

3.2.1 Infant mortality rate - modified and reported by county

Reported

3.2.2 Neonatal mortality rate - modified and reported by county

Reported

3.3 By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases

3.3.1 Number of new HIV infections by race reported at county - modified

Reported

3.3.2 Tuberculosis incidence per 100,000 population - modified

Reported

3.3.3 Malaria incidence per 1,000 population

Not applicable

3.3.4 Hepatitis B incidence rate reported at state level - modified

Reported

Figure 5.30: Goal 3 homepage

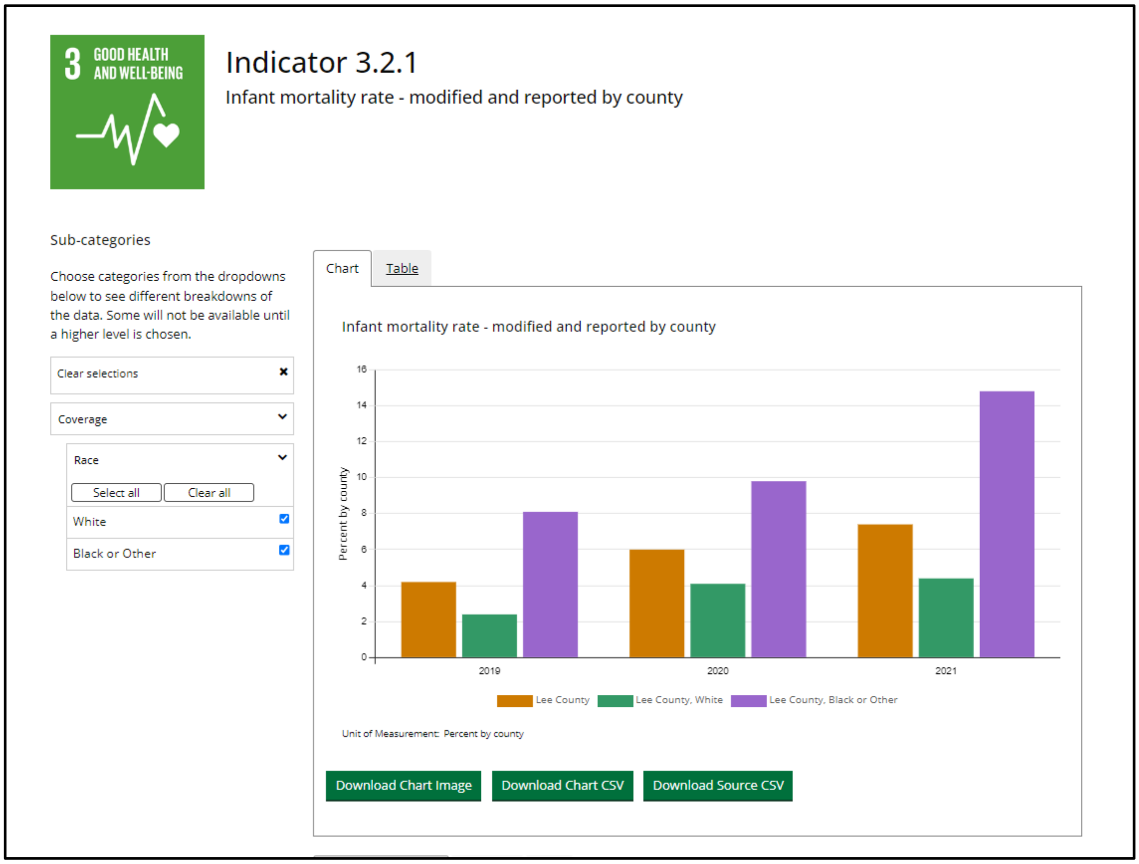


Figure 5.31: Indicator 3.2.1 page

National Metadata | Sources | Edit

This table provides metadata for the actual indicator available from %country_name statistics closest to the corresponding global SDG indicator. Please note that even when the global SDG indicator is fully available from %country_adjective statistics, this table should be consulted for information on national methodology and other %country_adjective-specific metadata information.

Goal	Goal 3: Ensure healthy lives and promote well-being for all at all ages
Target	Target 3.2: By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births
Indicator	Indicator 3.2.1: Infant mortality rate - modified and reported by county
Definition and concepts	**Limitations:** Alabama specifically does not report age specific children mortality rate but rather encompasses as infant mortality rate. Auburn does not report this statistics either and it is reported at county level.
Data providers	https://www.alabamapublichealth.gov/healthstats/assets/infantmortality2021.pdf
Data availability and disaggregation	Lee County, Al

Figure 5.32: Indicator 3.2.1 information page

Goal 4

Goal 4 titled "Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all" was primarily reported at the city level. Due to the unavailability of some information, the indicators had to be tailored to the information available from Auburn city School website (Figure 5.12). Additionally, the US Census and city-data.com were utilized to report some of the indicators for this goal. The visualization of the data in chart (bar) and table format, along with its metadata, for the indicator 4.3.1 is presented in Figure 5.13. A total of 6 indicators were reported, and 6 were deemed not applicable. To tailor to the reporting of Auburn city school, all of the indicators had to be modified from the UN standard. For instance, indicator 4.1.1 was modified to report at PK and Kindergarten level, indicator 4.1.2 was modified to report the percentage of high school and above completion, and indicator 4.2.2 was modified from percentage to numbers. Indicator 4.6.1 was modified to report the skills of third graders, while indicator 4.c.1 was modified to report the percentage of certified teachers, teacher to student ratio, and the ratio of full-time school counselors. Indicator 4.3.1 was reported as per the UN standard without taking the temporal component of 12 months into consideration.

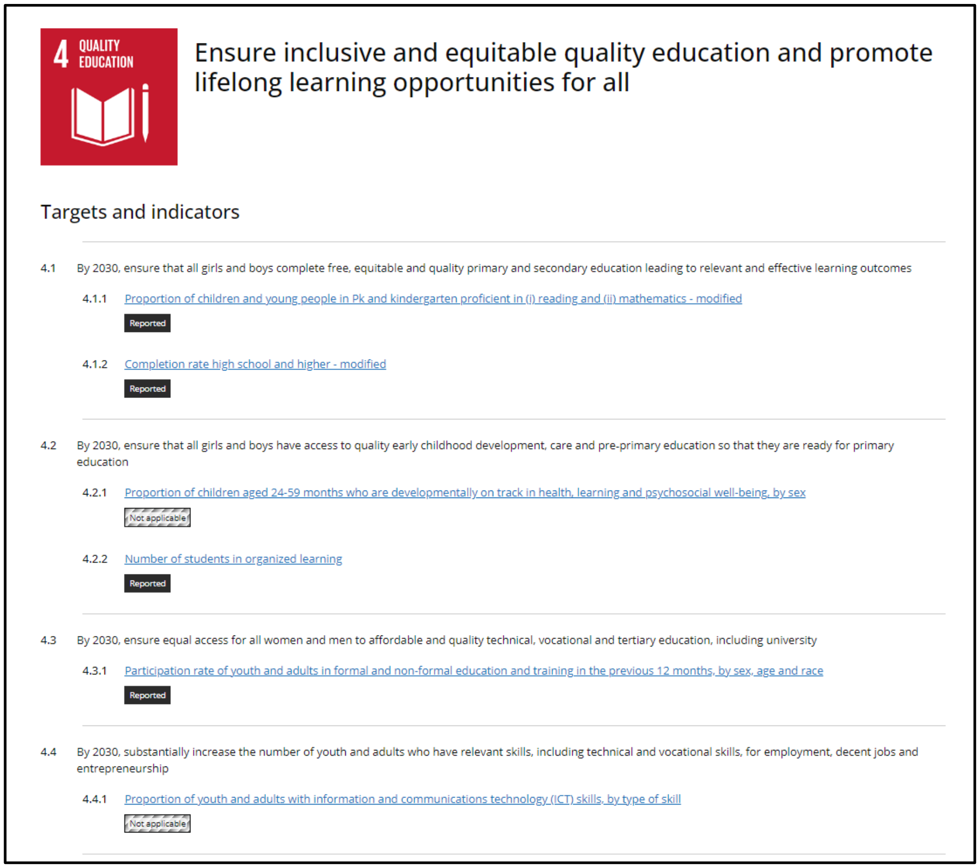


Figure 5.33: Goal 4 homepage

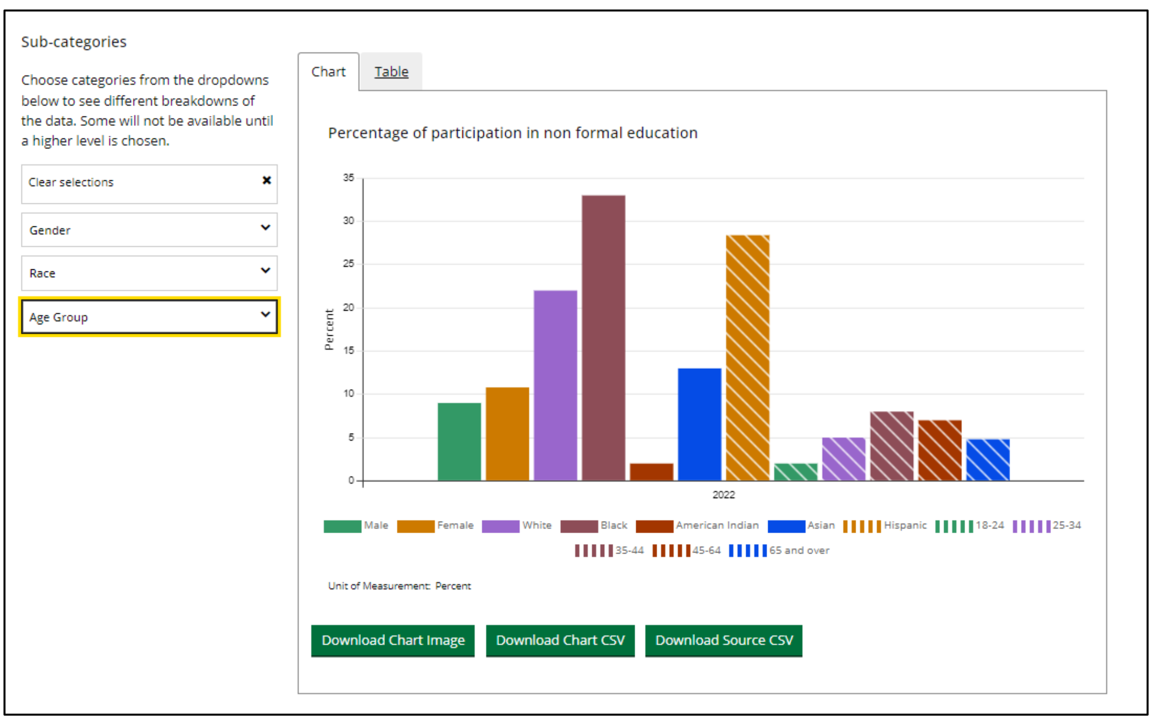
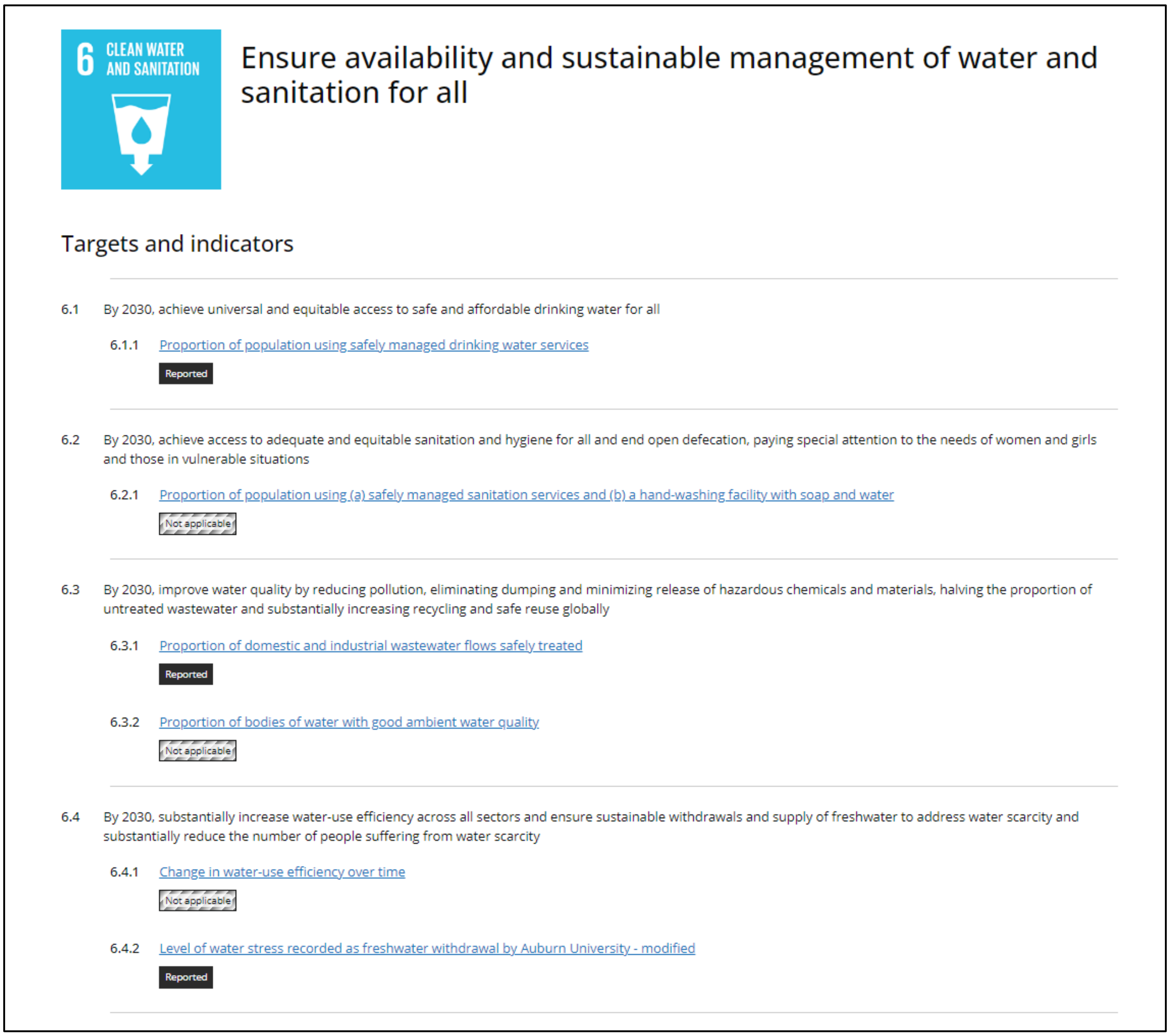


Figure 5.34: Indicator 4.3.1 page

Goal 6

Goal 6, titled "Ensure availability and sustainable management of water and sanitation for all," presented a unique challenge in terms of reporting at the city level (Figure 5.14). Auburn city's reporting primarily pertains to the safety of drinking water, making it difficult to find information about sustainable water usage, which is a major focus of the UN goal 6 indicators. Out of the 11 indicators, only 3 were able to be reported, and 1 had to be modified to report on Auburn University's water usage (Figure 5.15).



6 CLEAN WATER AND SANITATION

Ensure availability and sustainable management of water and sanitation for all

Targets and indicators

6.1 By 2030, achieve universal and equitable access to safe and affordable drinking water for all

6.1.1 Proportion of population using safely managed drinking water services

Reported

6.2 By 2030, achieve access to adequate and equitable sanitation and hygiene for all and end open defecation, paying special attention to the needs of women and girls and those in vulnerable situations

6.2.1 Proportion of population using (a) safely managed sanitation services and (b) a hand-washing facility with soap and water

Not applicable

6.3 By 2030, improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally

6.3.1 Proportion of domestic and industrial wastewater flows safely treated

Reported

6.3.2 Proportion of bodies of water with good ambient water quality

Not applicable

6.4 By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity

6.4.1 Change in water-use efficiency over time

Not applicable

6.4.2 Level of water stress recorded as freshwater withdrawal by Auburn University - modified

Reported

Figure 5.35: Goal 6 homepage

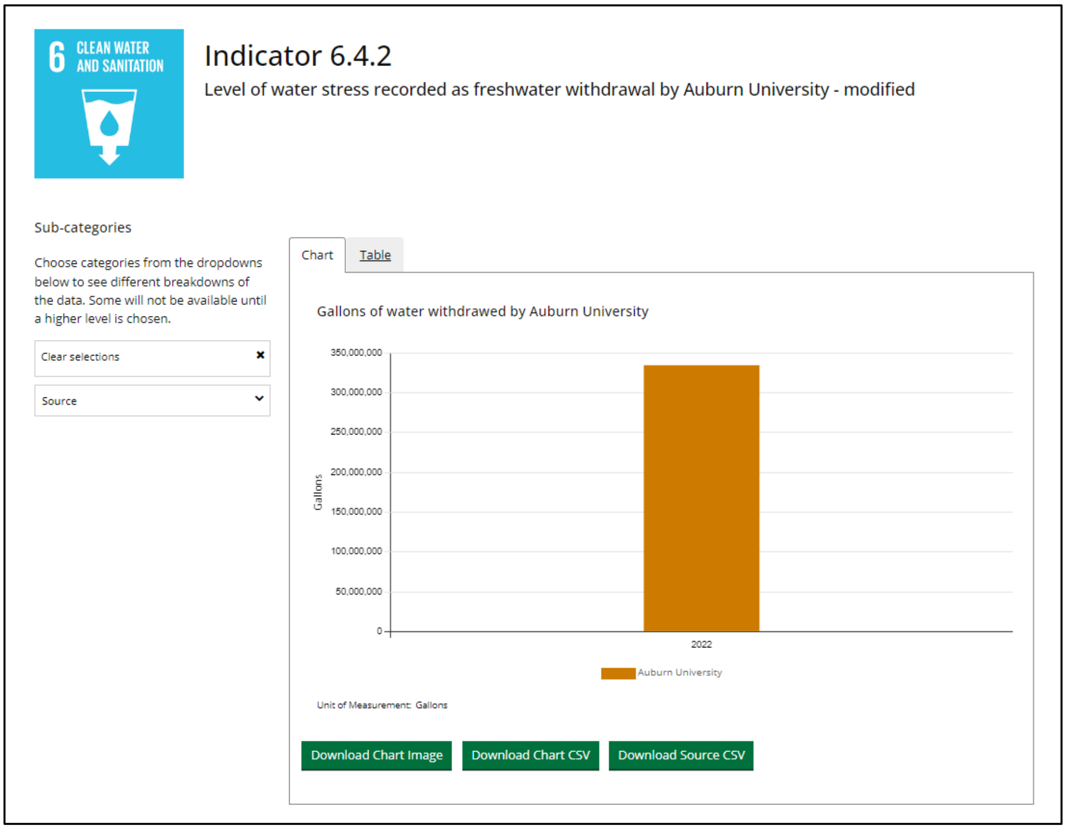
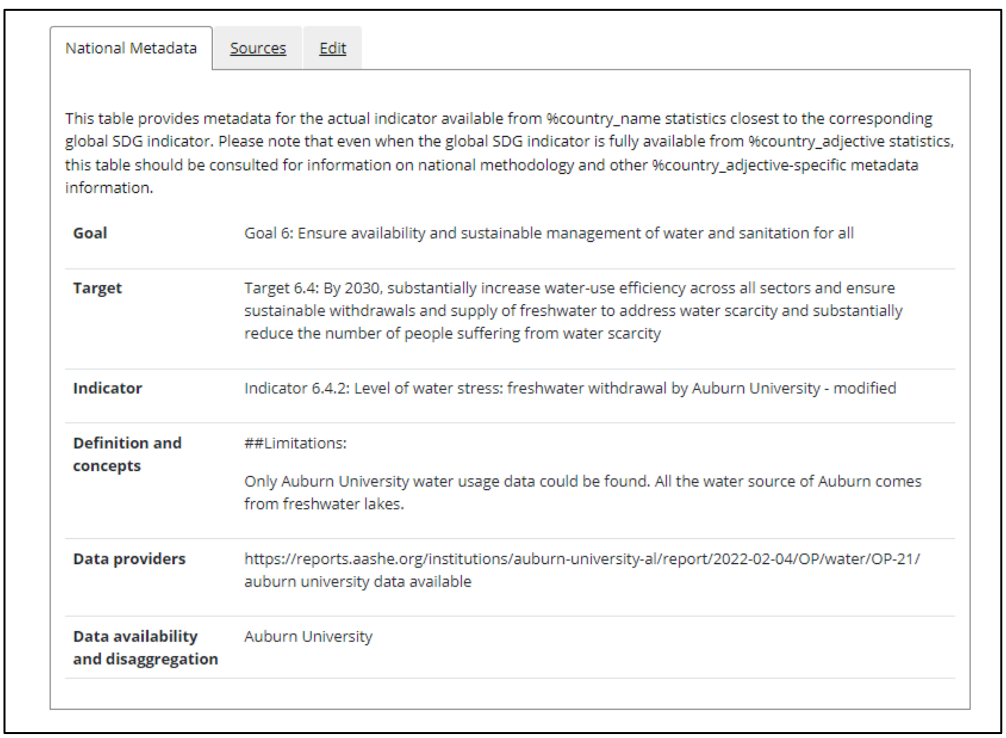


Figure 5.36: Indicator 6.4.2 page



National Metadata | Sources | Edit

This table provides metadata for the actual indicator available from %country_name statistics closest to the corresponding global SDG indicator. Please note that even when the global SDG indicator is fully available from %country_adjective statistics, this table should be consulted for information on national methodology and other %country_adjective-specific metadata information.

Goal	Goal 6: Ensure availability and sustainable management of water and sanitation for all
Target	Target 6.4: By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity
Indicator	Indicator 6.4.2: Level of water stress: freshwater withdrawal by Auburn University - modified
Definition and concepts	##Limitations: Only Auburn University water usage data could be found. All the water source of Auburn comes from freshwater lakes.
Data providers	https://reports.aashe.org/institutions/auburn-university-al/report/2022-02-04/OP/water/OP-21/ auburn university data available
Data availability and disaggregation	Auburn University

Figure 5.37: Indicator 6.4.2 information page

Goal 7

Goal 7, titled "Ensure access to affordable, reliable, sustainable, and modern energy for all," presents a complex set of challenges (Figure 5.17). The goal is focused on understanding energy access, usage, and the availability of renewable energy, which are all factors that vary greatly across different regions and countries. However, many of the indicators used to measure progress towards this goal are not applicable at a small city level, which can make it difficult to get a clear picture of what's happening on the ground. For example, indicators related to international financial flows to support clean energy or the installed renewable energy generating capacity in developing countries are not relevant to individual cities. As a result, only 2 out of 6 indicators were reported, 1 related to access to electricity in the city and the other related to the percentage of renewable energy use, which was modified to be reported at the state level (Figure 5.18).

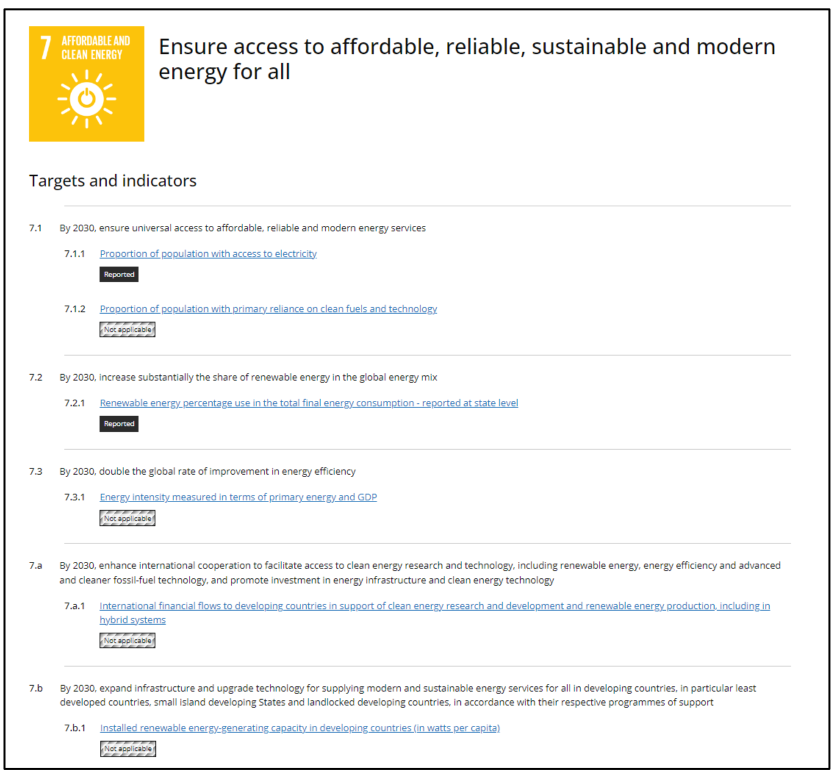


Figure 5.38: Goal 7 homepage

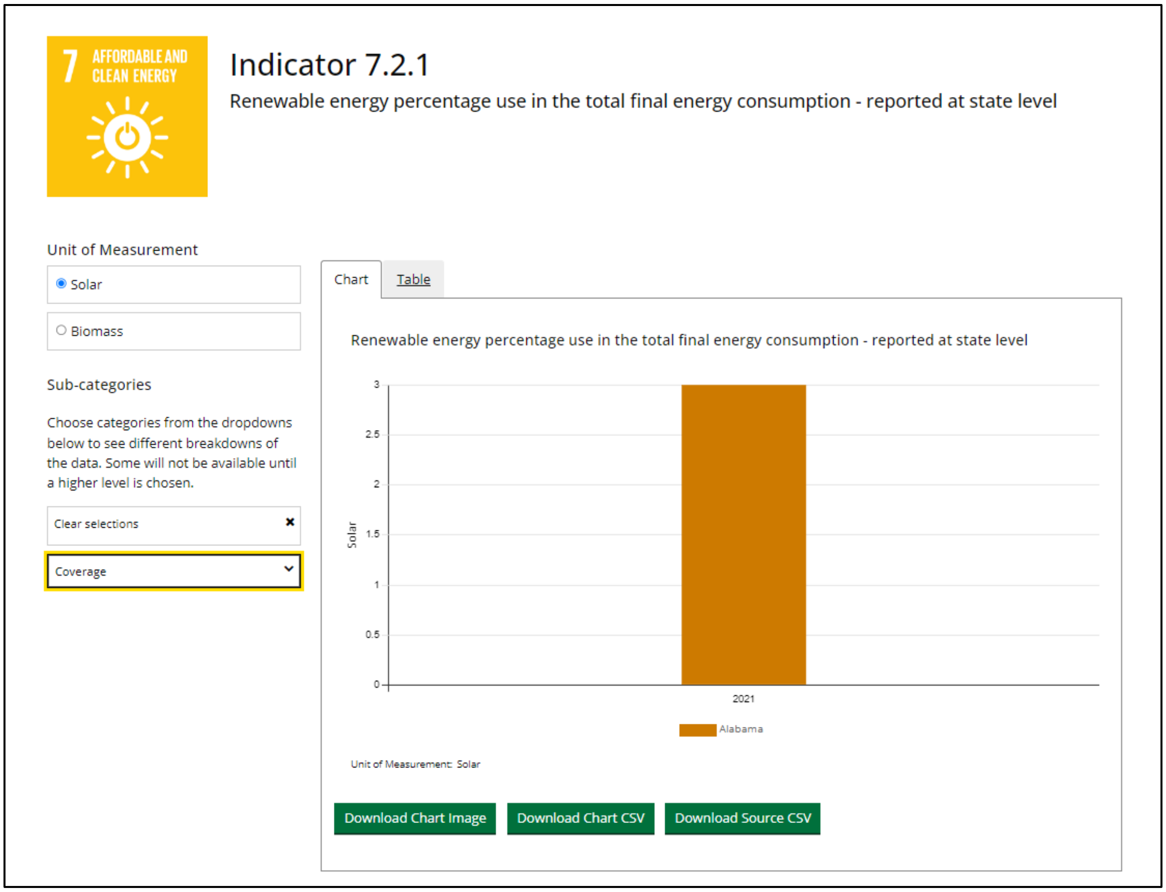


Figure 5.39: Indicator 7.2.1 page

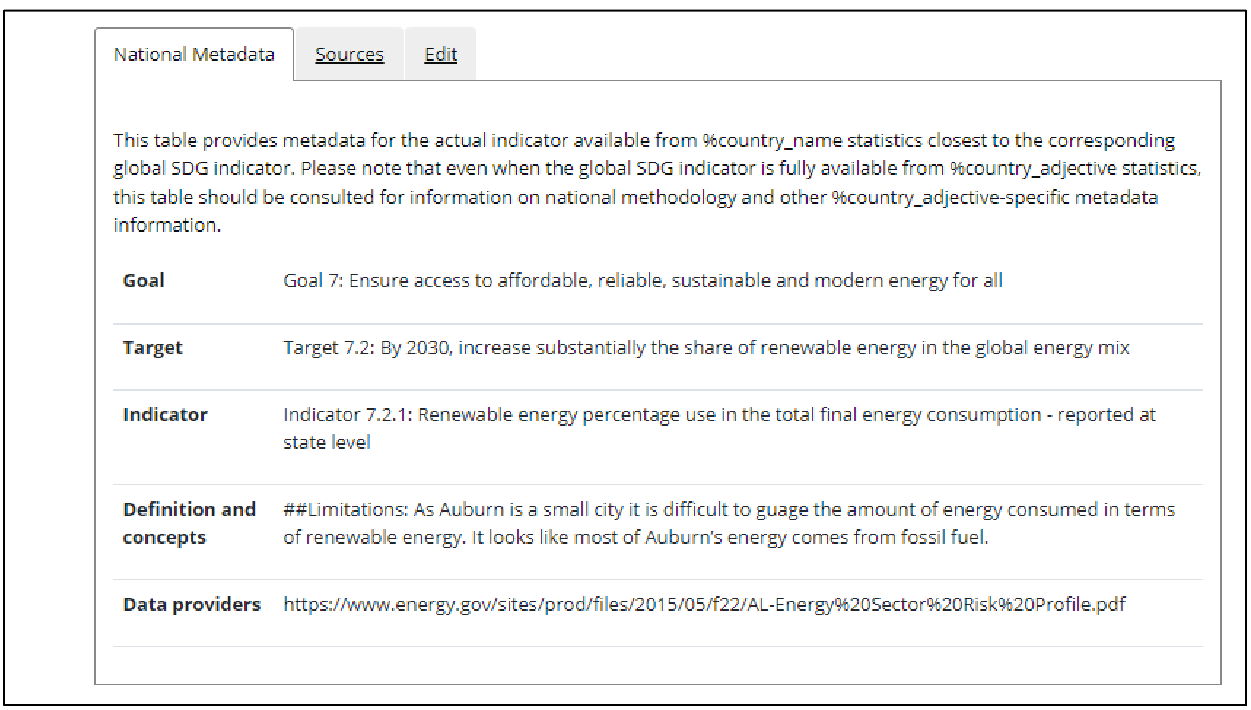


Figure 5.40: Indicator 7.2.1 information page

Goal 8

Goal 8, entitled "Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all," was predominantly reported at the city level, as depicted in Figure 5.20. All of the indicators associated with this goal were applicable at the city level, although only 7 out of 16 could be reported with some modifications based on the collected data. For instance, Indicator 8.1.1 only provided information on the annual growth rate in millions of chained 2012 dollars, while Indicator 8.3.1 provided information on informal employment by sector but not by sex. Furthermore, Indicator 8.5.1 was modified based on the type of occupation, while Indicator 8.5.2 was modified to report the overall unemployment rate rather than based on demographic distinctions. The other reported indicators were in accordance with UN standards.

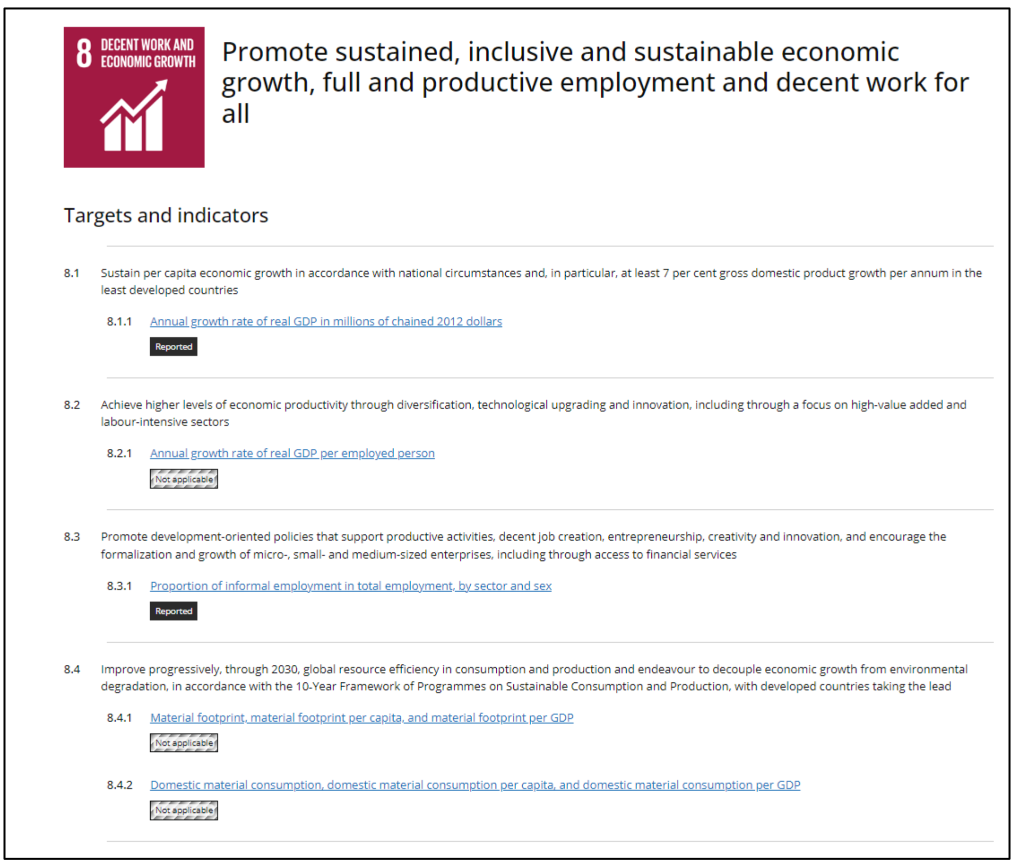


Figure 5.41: Goal 8 homepage

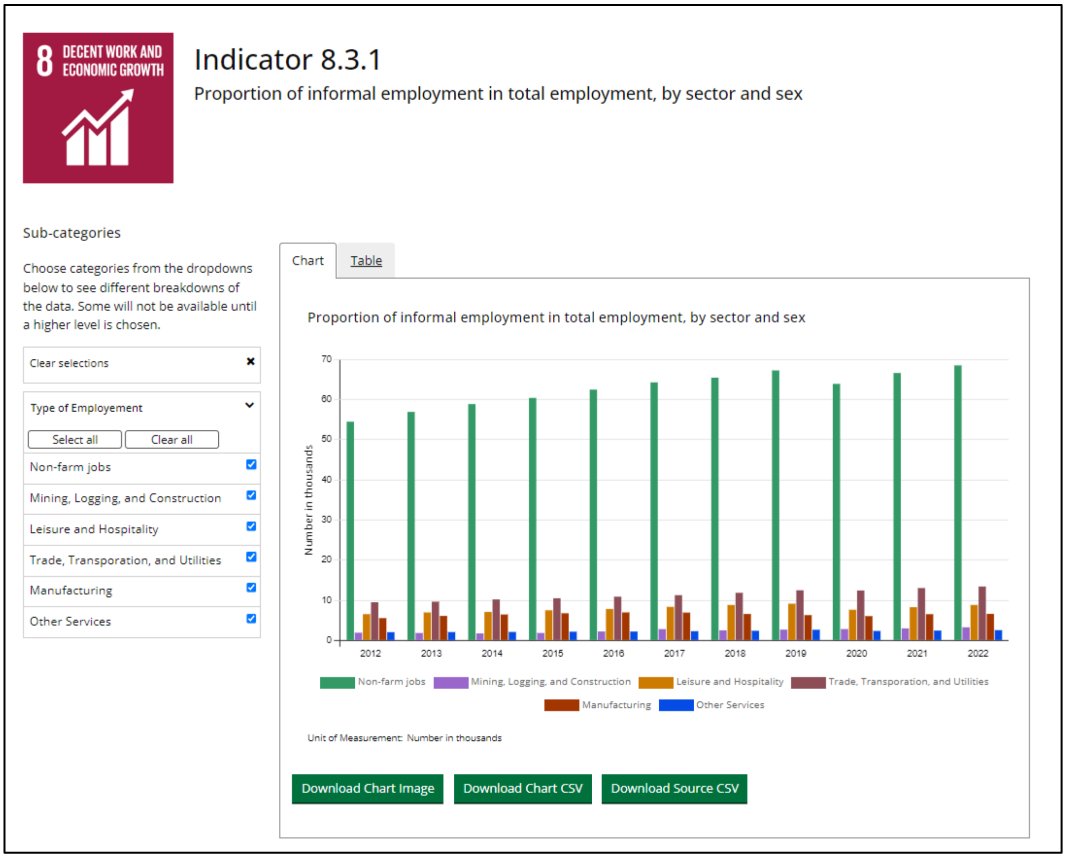
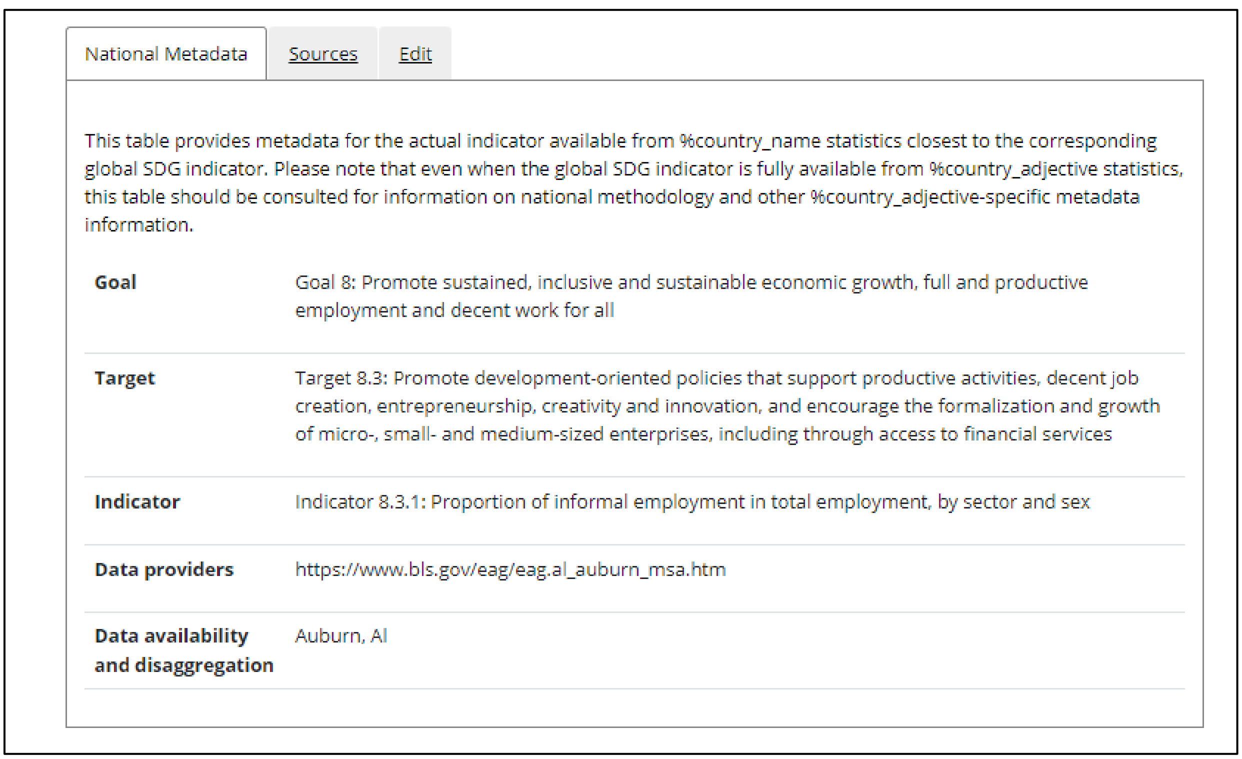


Figure 5.42: Indicator 8.3.1 page


National Metadata | Sources | Edit

This table provides metadata for the actual indicator available from %country_name statistics closest to the corresponding global SDG indicator. Please note that even when the global SDG indicator is fully available from %country_adjective statistics, this table should be consulted for information on national methodology and other %country_adjective-specific metadata information.

Goal	Goal 8: Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all
Target	Target 8.3: Promote development-oriented policies that support productive activities, decent job creation, entrepreneurship, creativity and innovation, and encourage the formalization and growth of micro-, small- and medium-sized enterprises, including through access to financial services
Indicator	Indicator 8.3.1: Proportion of informal employment in total employment, by sector and sex
Data providers	https://www.bls.gov/eag/eag.al_auburn_msa.htm
Data availability and disaggregation	Auburn, Al

Figure 5.43: Indicator 8.3.1 information page

Discussion

This chapter describes the development and analysis of an open SDG data reporting platform for small cities, using Auburn City as an example to report on the UN Sustainable Development Goals (SDGs) at a small city level. The study found that out of 99 indicators spanning 7 goals, 41 could be reported, while 58 were not applicable. This highlights the importance of adapting the SDGs to specific contexts, such as cities, as different regions, countries, and cities report information at varying spatial, temporal, and cultural scales. The analysis provides specific examples of how each of the SDGs was reported in Auburn, with a focus on goals 1, 2, 3, 4, 6, 7, and 8.

For instance, in reporting on goal 1, which aims to end poverty in all its forms everywhere, the study found that some indicators required modification to reflect the poverty standard in the US, while few had to be adjusted to report at the state level since the information was not readily available at the city level. Goal 2, which aims to end hunger, achieve food security, and promote sustainable agriculture, required the use of a privately-owned and operated City-Data website due to the limited availability of information regarding food security and nutrition at the city level. Additionally, only three out of 14 indicators could be reported, highlighting the need for more accessible and publicly available data sources for small cities to report on the SDGs accurately.

Goal 3, which aims to ensure healthy lives and promote well-being for all at all ages, was mostly modified to report at the county and state level due to the lack of health-related information at the city level. The study notes that the lack of health-related information at the city level could be due to the absence of a large hospital in the city, with the nearest one being in Auburn and Opelika. Goals 6 and 7, which address sustainable management of water and sustainable and modern energy accessibility, respectively, were found to be the most challenging to report, with modifications needed due to differences in reporting standards between Auburn city and the UN. The study found that most of the indicators addressing goal 8, which focuses on sustained, inclusive, and sustainable economic growth, were reported at the city level, with some needing modification and others deemed irrelevant.

Despite the challenges of reporting the UN SDGs at a small city level, such as the lack of available data or different reporting standards, it is essential to provide a framework for monitoring progress towards sustainable development. The use of the open SDG data reporting platform provides a useful tool for cities to report their progress towards the SDGs and identify areas of improvement. However, it is crucial to recognize that the SDGs must be adapted to specific contexts, and modifications may be necessary to reflect the local situation accurately. The findings suggest that there may be room for improvement in data collection and reporting at the small city level, for example, for goals 6 and 7 in Auburn, AL, where there were significant challenges to reporting. Therefore, efforts to improve data collection, data quality, and reporting at the small city level could be beneficial in ensuring progress towards a sustainable and resilient development and creating an effective UIS. Additionally, more efforts are needed to harmonize data collection and management standards across regions to ensure consistency in reporting.

Limitations

The study has several limitations that must be considered when interpreting the findings. Firstly, the study was conducted in a single small city, Auburn, AL, which may not be representative of other small cities in different regions or countries. The study is also conducted by a single researcher, compared to city, states, or country officials themselves, so it is more challenging (Koch and Kullenberg). While the findings of this study provide valuable insights into the challenges and opportunities of reporting on the SDGs at the small city level, caution must be exercised in generalizing the results to other contexts. Additionally, the study identified a lack of available data at the city level for some of the SDGs, which made it difficult to report accurately on those goals. This limitation may have impacted the accuracy and completeness of the findings. While efforts were made to gather data from various sources, some indicators remained unreported due to a lack of available data. This highlights the need for more accessible and publicly available data sources to facilitate more accurate and comprehensive reporting on the SDGs at the small city level. Furthermore, the study also found that there were differences in reporting standards between the UN and Auburn City, which required modifications to be made to some of the indicators. These modifications may have affected the comparability of the findings with other cities or regions. While the study attempted to adjust the reporting of the indicators to align with the UN's standards, differences in reporting standards may have introduced variability in the results. Therefore, further efforts are needed to harmonize data collection and management standards across regions to ensure consistency in reporting. Fourthly, the analysis of the data was based on the interpretation of the researchers, which may have introduced subjectivity and bias into the results. While efforts were made to minimize bias, subjective interpretations of the data may have influenced the findings. Future studies may benefit from employing multiple researchers to analyze the data independently to mitigate the effects of bias. Lastly, the study did not have a control group or comparison group against which to compare the findings, which may limit the ability to draw strong conclusions about the effectiveness of the open SDG data reporting platform. Future studies may benefit from including a control or comparison group to help establish a baseline against which to compare the findings.

Therefore, while the findings of this study provide important insights into the challenges and opportunities of reporting on the SDGs at the small city level, it is important to recognize and account for the limitations of the study to avoid overgeneralizing the results. Future research may benefit from addressing these limitations to improve the accuracy and generalizability of the findings.

Conclusion

In conclusion, the analysis highlights the need for more accessible and publicly available data sources for small cities to report on the SDGs accurately. It also emphasizes the importance of adapting the SDGs to specific contexts such as cities, which report information at varying spatial, temporal, and cultural scales. Finally, the analysis calls for better coordination and consolidation of data sources to make reporting more manageable and consistent across different SDGs, especially for health-related indicators.

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CHAPTER 6: CONCLUSION

Sustainability can be defined as the ability of a system to continue functioning and providing benefits to its stakeholders over the long term, without compromising the well-being of future generations or the natural systems upon which they depend. United Nations came up with 17 sustainable development goals with the aspiration of being achieved by all by 2030 based on the everchanging landscapes, population increase, economic disparity, climate change, social inequality, and health concerns to name a few. The studies that compose this dissertation tackle sustainable development in three different ways: social, physical, and informational. Together, these studies create a framework that small and medium-sized cities in SEUS can follow to promote community engagement, comprehend their everchanging urban landscape with a look at the future, and visualize their efforts in a standardized and efficient manner to promote transparency and accountability by identifying the areas of gaps and needed improvements.

The first study focused on the development and testing of an instrument designed to assess community attributes and attitudes pertaining to sustainability utilizing UN SDGs. The study documents the design process and outlines how classical test theory was used to establish evidence of reliability and validity. The results of the instrument development process indicate that for residents of the southeastern US, the construction of knowledge about SDGs was not relevant. The design process provided us with content inventory which can be used by any governing body in SEUS. The design process yielded a content inventory that can be used by governing bodies in the southeastern US. The instrument developed in this study represents a significant step forward for the region to collect and analyze citizen attributes and attitudes towards sustainability, thereby improving community engagement. This allows for many new opportunities for research aimed at sustainable development. These studies not only enhance our understanding of residents' attributes and attitudes but also offer insight into exciting future research opportunities. The development of the Sustainability Survey concept inventory provides the tool for assessing the awareness/familiarity, concern/urgency, perception, intended behavior, involvement, and behavior towards SDGs. The inventory also provides a way to assess differences among demographic groups, which is analyzed in Chapter 2 to create targeted plans and policies for encouraging community engagement for sustainability by governing bodies. In a broader sense, the development of the concept inventory allows other researchers and governing bodies to quantitatively assess sustainability thinking abilities both in terms of how they currently assess sustainability and as a result of creating targeted interventions to promote sustainable thinking.

The second study employed multigroup confirmatory factor analysis and structural equation modeling to examine group differences within three demographic groups – gender, political affiliation, and income level – and the relationship between latent variables related to awareness/familiarity, concern/urgency, perception, intended behavior, involvement, and behavior based on 936 valid responses from the survey created in the first study. The results revealed significant differences within the groups. Female participants demonstrated more concern, behavioral characteristics, were more likely to be involved, and developed substantial behavior towards sustainability, even though the level of awareness about sustainability was similar between male and female respondents. It was also found that high-income individuals demonstrated more concern, behavior, and were more likely to be involved in creating future behavior towards sustainability than low-income individuals, although the level of awareness between the groups was similar. A satisfactory model with respect to political affiliation could not be established. It is important to note that the analysis has limitations, and therefore, the results should be interpreted with caution. Additionally, the full structural equation model that was developed found that concern/urgency are the most influential constructs for current and future behavior towards sustainability. This suggests that governing bodies should focus on emphasizing the urgency and concern towards changing landscapes, economic disparity, health concerns, hazards, work opportunities, to encourage sustainable behavior.

The third study explored the usage of machine learning and remote sensing techniques to investigate the dynamic nature of the urban landscape of one of the SEUS states, Alabama. The study analyzed the landcover change over the years and projected future scenarios for the 10 most populous cities of Alabama. The rationale for choosing Alabama was to demonstrate that even in one of the most underdeveloped and impoverished states in the US, urban areas are rapidly changing with an increase in impervious surfaces, thereby augmenting the risk of climate-related disasters. Moreover, the study was conducted to highlight the potential consequences of a business-as-usual scenario in the absence of sustainable development interventions, thereby illustrating the environmental changes that can occur in a region without any consideration for sustainable planning.

The final study of this dissertation shifted its focus to Auburn, a small city in the state of Alabama. As a university town, it provided a unique opportunity to analyze and visualize the current state of sustainable plans, policies, and efforts of a small city. This approach provided a centralized, standardized, efficient, and effective data visualization tool which helped identify gaps and challenges towards reporting SDGs at such a small scale. While SDGs are created for a national scale, understanding their applicability at a local scale such as a city is important as cities are the breeding ground for activation, innovation, and changes. In the case of Auburn, Alabama, it was noted that some of the indicators were not applicable at this scale, and many of them had to be modified. Moreover, most of the datasets found were from non-governmental sites which can introduce bias in the collected data.

The increasing urbanization worldwide has resulted in more than 50% of the world's population living in urban areas, and this trend is projected to continue. Therefore, to achieve a sustainable future for all, cities must be the focus of sustainable development studies. The studies presented in this dissertation focused on three different spatial scales - regional, state, and city - and three different elements - social, physical, and informational - with a focus on aggregating all its analysis at a city scale at the end. This work is critical, as through developing content inventory for a sustainable survey, analyzing the responses from SEUS citizens, analyzing the ever-changing urban landscape of Alabama cities, and creating a centralized and standardized visualization of SDG indicators for Auburn, it creates a framework that any small and medium-sized cities in SEUS can follow towards achieving sustainable development goals by engaging their communities, understanding environmental changes, and establishing communication systems with their citizens.

APPENDICES

Appendix A

Questionnaire

Pilot Survey

3/2/23, 10:37 AM Qualtrics Survey Software

AUBURN UNIVERSITY

Question Tour Block 1

Information Letter

City Sustainability Survey

Introduction

The purpose of this study is to create valid and reliable survey instrument that could be potentially used by small and medium size cities across Southeast USA (SEUS) to (1) determine Southeast US (SEUS) residents' awareness, knowledge, concern, intent, intended behavior, and perceptions about sustainability and the Sustainability Development Goals (https://sdgs.un.org/goals) and better understand the association using a volunteer convenience sample; (2) ascertain whether or if characteristics such as political or religious orientation, gender, income level or educational level influenced residents' responses; and (3) provide a means to the city to collect such information that can guide present and future development plans and policies.

https://auburn.yul1.qualtrics.com/Q/EditSection/Blocks/Ajax/GetSurveyPrintPreview?ContextSurveyID=SV_e58rS0skYQT831I&ContextLibraryID=UR... 1/21

Individuals who meet the following criteria are encouraged to participate: Adults (age 18 years and above) who is living in Southeast USA and cares about the well-being of their cities is encouraged to participate.

Participation

Participation in this research study is completely voluntary. You have the right to withdraw at any time or refuse to participate. If you desire to withdraw, please close your internet browser.

The questions may seem similar but there are subtle differences in the result outputs. So the participants should not think the questions are repetitive.

Procedures

The purpose of this survey is to gain an understanding about Southeast USA citizens awareness, knowledge, perception, and concern about sustainability practices in the city they live in. You will be asked to complete a questionnaire that consists of 28 questions that will take approximately 10-15 minutes to complete. This questionnaire will be conducted with an online Qualtrics-created survey.

Risks/Discomforts

Risks are minimal for involvement for this study; however, you may feel emotionally uneasy when asked to answer questions about careers and age. You should seek help from your primary care provider for any distress experienced. Please note that you are responsible for any costs related to this care. You will not be asked to identify yourself in this study.

Benefits

There are no direct benefits for participation in this study; however, it is hoped that through your participation, researchers will create a better plan for sustainable and resilient cities of Southeast USA.

Confidentiality

All data obtained from participants will be kept confidential and will only be reported in summary format (no single individual's responses will be reported). The survey does not collect any personal information of the participants so the data collected are all anonymous and will also be reported in terms of plots and graphs rather than individual responses.

Compensation

Participants will be compensated $0.50 per survey.

Questions about the Research

If you have questions regarding the study, you may contact Megha Shrestha, Ph.D. student at mzs0130@auburn.edu or her advisor, Chandana Mitra, Ph.D. at czm0033@auburn.edu, Department of Geosciences, Auburn University.

Questions about your Rights as a Research Participant

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Human Subjects Research or the Institutional Review Board by phone (334) 844-5966 or email at hsubjec@auburn.edu or IRBChair@auburn.edu. HAVING READ THE INFORMATION ABOVE, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS RESEARCH PROJECT. IF YOU DECIDE TO PARTICIPATE, PLEASE CLICK ON THE LINK BELOW. YOU MAY PRINT A COPY OF THIS LETTER TO KEEP.

https://auburn.qualtrics.com/jfe/form/SV_e58rS0skYQT831I

Please use your Amazon MTurk worker id at the end of the survey.

The Auburn University Institutional Review Board has approved this document for use on Approved Protocol, AU IRB #22-138 EX 2204, Shrestha.

Which U.S region do you live in?

Theme 1: Awareness and Familiarity

The awareness and familiarity theme is intended to understand the community's awareness and familiarity of the United Nations' Sustainable Development Goals (UN SDGs). Please indicate your familiarity with each of the below statements.

Q1. I am familiar with the term "Sustainable Development Goals (SDGs)".

- Very familiar
- Familiar
- Slightly familiar
- Unfamiliar
- Very unfamiliar

Q2. I am aware of the fact that Sustainable Development Goals are targeted to be achieved by the year 2030.

- Strongly Agree
- Agree
- Slightly Agree
- Disagree
- Strongly Disagree

Q3. I recognize the following as SDGs.

	Strongly Agree	Agree	Slightly Agree	Disagree	Strongly Disagree
No poverty	○	○	○	○	○
Zero hunger	○	○	○	○	○
Good health and well -being	○	○	○	○	○
Quality education	○	○	○	○	○
Clean water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○
Equality	○	○	○	○	○
Education	○	○	○	○	○
Partnership	○	○	○	○	○

	Strongly Agree	Agree	Slightly Agree	Disagree	Strongly Disagree
Wealth redistribution	◯	◯	◯	◯	◯
Economic opportunities	◯	◯	◯	◯	◯
Universal health care	◯	◯	◯	◯	◯
Eliminating food desert	◯	◯	◯	◯	◯
Ending gun violence	◯	◯	◯	◯	◯
Carbon tax	◯	◯	◯	◯	◯
Guarantee minimum wage	◯	◯	◯	◯	◯

Theme 2: Concern and Urgency

The concern and urgency theme is intended to measure the community's concern and urgency about socioeconomic and environmental changes due to various issues in their cities. Please indicate how concerned you are with each of the below statements.

Q4. I am concerned

	Extremely concerned	Concerned	Slightly concerned	Unconcerned	Extremely unconcerned
about cost of housing	○	○	○	○	○
About cost of education	○	○	○	○	○
About quality of K12 education	○	○	○	○	○
About health insurance rate	○	○	○	○	○
About not having enough supermarkets/fresh food	○	○	○	○	○
About nutritional value of food in my community	○	○	○	○	○
About level of food waste in my community	○	○	○	○	○
About hospital/medical access in my community	○	○	○	○	○
About women's healthcare in my community	○	○	○	○	○
About the wasteful consumption of natural resources	○	○	○	○	○
About the destruction/ pollution of the environment	○	○	○	○	○
About how my drinking water is treated in my community	○	○	○	○	○

	Extremely concerned	Concerned	Slightly concerned	Unconcerned	Extremely unconcerned
About underground water utilities in my community	○	○	○	○	○

Q5. I believe my state government should do more to address

	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well-being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Q6. How important is solving the following issues to you?

	Very important	important	Slightly important	Unimportant	Very unimportant
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○

	Very important	important	Slightly important	Unimportant	Very unimportant
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Q7. How urgent is solving the following issues to you?

	Extremely urgent	Urgent	Slightly urgent	trivial	Extremely trivial
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Validation check: What is 2+4?

Theme 3: Intended Behavior - Engagement

The intended behavior - engagement theme is designed to understand whether the community thinks the issues below need to be addressed. Please indicate how much you believe in following statements: Strongly Agree = will engage; Strongly Disagree = No engagement

Q8. I am willing to protest for following issues.

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Decent work and economic growth	○	○	○	○	○

Q9. I am willing to pay more for sustainable goods and services.

- ○ Strongly Agree
- ○ Agree
- ○ Slightly Agree
- ○ Disagree
- ○ Slightly Disagree

Q10. I am willing to engage with my congress person for following issues.

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Theme 4: Involvement

The involvement theme is expected to help understand the participant's involvement to act in solving various mentioned issues. Please indicate if you take action in resolving the issues below.

Q11. I currently take specific action to make my community more sustainable with respect to achieving following goals.

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Validation Check: What is 4+2?

Theme 5: Perception

The perception theme is intended to understand the participant's perception about solving the issues. Please indicate how optimistic you are in solving the mentioned issues are for your city.

Q12. How optimistic are you that the issues will improve?

	Extremely optimistic	Optimistic	Slightly optimistic	pessimistic	Extremely pessimistic
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○

	Extremely optimistic	Optimistic	Slightly optimistic	pessimistic	Extremely pessimistic
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Theme 6: Behavior

The behavior theme is intended to understand the participant's behavioral pattern about solving the issues. Please indicate how likely would you take action in resolving the issues below.

Q13. I currently conserve the use of electric energy at my home.

- ○ Strongly Agree
- ○ Agree
- ○ Slightly Agree
- ○ Disagree

- Strongly Disagree

Q14. I want to help make my community be more sustainable.

- Strongly Agree
- Agree
- Slightly agree
- Disagree
- Strongly Disagree

Q15. I would like to conserve the use of electric energy at my house.

- Strongly Agree
- Agree
- Slightly agree
- Disagree
- Strongly Disagree

Q16. The following SDGs will be achieved within 10 years in your community.

	Strongly agree	Agree	Neutral	disagree	Strongly disagree
Poverty	○	○	○	○	○

	Strongly agree	Agree	Neutral	disagree	Strongly disagree
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Theme 6: Demographics

Next, we will collect some demographic information. Note that preferring to not disclose is an option for every item.

Q17. State you live in.

Q18. City you live in

Q19. Zip code of the place you live in

Q20. Highest Education Level Completed

- High school
- Bachelors
- Community College/Trade School
- Graduate
- Postgraduate and above
- Other
- Decline to state

Q21. Please tell us your age

Q22. Occupation

Q23. Gender

- Male
- Female
- Non-binary
- Decline to state

Q24.Sexuality

- Asexual
- Bisexual
- Gay
- Heterosexual or Straight
- Lesbian
- Pansexual
- Queer
- None of the above, please specify

Q25. Political affiliation

- Very conservative
- somewhat conservative/right leaning
- middle of the road
- somewhat liberal/left leaning
- very liberal/progressive

Q26. Race

- American Indian or Alaska Native
- Asian
- Black or African American
- Native Hawaiian or Other Pacific Islander
- White
- more than one race/ethnicity

Q27. Income Level of the individual

- <25,000
- 25,000-49,999
- 50,000-69,999
- 75,000-99,999
- >100,000

Q28. How did you find out about the survey?

Thank you for your time.

Here is your Mechanical Turk Code:

SMSC-${e://Field/MechanicalTurkID}-AU

Sorry for the inconvenience. We won't be able to take your response for this survey.

Powered by Qualtrics

Main Survey

AUBURN UNIVERSITY

Question Tour Block 1

Information Letter

City Sustainability Survey

Introduction

The purpose of this study is to create valid and reliable survey instrument that could be potentially used by small and medium size cities across Southeast USA (SEUS) to (1) determine Southeast US (SEUS) residents' awareness, knowledge, concern, intent, intended behavior, and perceptions about sustainability and the Sustainability Development Goals (https://sdgs.un.org/goals) and better understand the association using a volunteer convenience sample; (2) ascertain whether or if characteristics such as political or religious orientation, gender, income level or educational level influenced residents' responses; and (3) provide a means to the city to collect such information that can guide present and future development plans and policies.

Individuals who meet the following criteria are encouraged to participate: Adults (age 18 years and above) who is living in Southeast USA and cares about the well-being of their cities is encouraged to participate.

Participation

Participation in this research study is completely voluntary. You have the right to withdraw at any time or refuse to participate. If you desire to withdraw, please close your internet browser.

The questions may seem similar but there are subtle differences in the result outputs. So the participants should not think the questions are repetitive.

Procedures

The purpose of this survey is to gain an understanding about Southeast USA citizens awareness, knowledge, perception, and concern about sustainability practices in the city they live in. You will be asked to complete a questionnaire that consists of 28 questions that will take approximately 10-15 minutes to complete. This questionnaire will be conducted with an online Qualtrics-created survey.

Risks/Discomforts

Risks are minimal for involvement for this study; however, you may feel emotionally uneasy when asked to answer questions about careers and age. You should seek help from your primary care provider for any distress experienced. Please note that you are responsible for any costs related to this care. You will not be asked to identify yourself in this study.

Benefits

There are no direct benefits for participation in this study; however, it is hoped that through your participation, researchers will create a better plan for sustainable and resilient cities of Southeast USA.

Confidentiality

All data obtained from participants will be kept confidential and will only be reported in summary format (no single individual's responses will be reported). The survey does not collect any personal information of the participants so the data collected are all anonymous and will also be reported in terms of plots and graphs rather than individual responses.

Compensation

Participants will be compensated $0.50 per survey.

Questions about the Research

If you have questions regarding the study, you may contact Megha Shrestha, Ph.D. student at mzs0130@auburn.edu or her advisor, Chandana Mitra, Ph.D. at czm0033@auburn.edu, Department of Geosciences, Auburn University.

Questions about your Rights as a Research Participant

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Human Subjects Research or the Institutional Review Board by phone (334) 844-5966 or email at hsubjec@auburn.edu or IRBChair@auburn.edu. HAVING READ THE INFORMATION ABOVE, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS RESEARCH PROJECT. IF YOU DECIDE TO PARTICIPATE, PLEASE CLICK ON THE LINK BELOW. YOU MAY PRINT A COPY OF THIS LETTER TO KEEP.

https://auburn.qualtrics.com/jfe/form/SV_e58rS0skYQT831I

Please use your Amazon MTurk worker id at the end of the survey.

The Auburn University Institutional Review Board has approved this document for use on Approved Protocol, AU IRB #22-138 EX 2204, Shrestha.

Which U.S region do you live in?

Theme 1: Awareness and Familiarity

The awareness and familiarity theme is intended to understand the community's awareness and familiarity of the United Nations' Sustainable Development Goals (UN SDGs). Please indicate your familiarity with each of the below statements.

Q1. I am familiar with the term "Sustainable Development Goals (SDGs)".

- Very familiar
- Familiar
- Slightly familiar
- Unfamiliar
- Very unfamiliar

Q2. I am aware of the fact that Sustainable Development Goals are targeted to be achieved by the year 2030.

- ○ Strongly Agree
- ○ Agree
- ○ Slightly Agree
- ○ Disagree
- ○ Strongly Disagree

Q3. I recognize the following as SDGs.

	Strongly Agree	Agree	Slightly Agree	Disagree	Strongly Disagree
No poverty	○	○	○	○	○
Zero hunger	○	○	○	○	○
Good health and well -being	○	○	○	○	○
Quality education	○	○	○	○	○
Clean water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○
Equality	○	○	○	○	○
Education	○	○	○	○	○
Partnership	○	○	○	○	○

	Strongly Agree	Agree	Slightly Agree	Disagree	Strongly Disagree
Wealth redistribution	○	○	○	○	○
Economic opportunities	○	○	○	○	○
Universal health care	○	○	○	○	○
Eliminating food desert	○	○	○	○	○
Ending gun violence	○	○	○	○	○
Carbon tax	○	○	○	○	○
Guarantee minimum wage	○	○	○	○	○

Theme 2: Concern and Urgency

The concern and urgency theme is intended to measure the community's concern and urgency about socioeconomic and environmental changes due to various issues in their cities. Please indicate how concerned you are with each of the below statements.

Q4. I am concerned

	Extremely concerned	Concerned	Slightly concerned	Unconcerned	Extremely unconcerned
about cost of housing	○	○	○	○	○
About cost of education	○	○	○	○	○
About quality of K12 education	○	○	○	○	○
About health insurance rate	○	○	○	○	○
About not having enough supermarkets/fresh food	○	○	○	○	○
About nutritional value of food in my community	○	○	○	○	○
About level of food waste in my community	○	○	○	○	○
About hospital/medical access in my community	○	○	○	○	○
About women's healthcare in my community	○	○	○	○	○
About the wasteful consumption of natural resources	○	○	○	○	○
About the destruction/ pollution of the environment	○	○	○	○	○
About how my drinking water is treated in my community	○	○	○	○	○

	Extremely concerned	Concerned	Slightly concerned	Unconcerned	Extremely unconcerned
About underground water utilities in my community	○	○	○	○	○

Q5. I believe my state government should do more to address

	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well-being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Q6. How important is solving the following issues to you?

	Very important	important	Slightly important	Unimportant	Very unimportant
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○

	Very important	important	Slightly important	Unimportant	Very unimportant
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Q7. How urgent is solving the following issues to you?

	Extremely urgent	Urgent	Slightly urgent	trivial	Extremely trivial
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Validation check: What is 2+4?

Theme 3: Intended Behavior - Engagement

The intended behavior - engagement theme is designed to understand whether the community thinks the issues below need to be addressed. Please indicate how much you believe in following statements: Strongly Agree = will engage; Strongly Disagree = No engagement

Q8. I am willing to protest for following issues.

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Decent work and economic growth	○	○	○	○	○

Q9. I am willing to pay more for sustainable goods and services.

- ○ Strongly Agree
- ○ Agree
- ○ Slightly Agree
- ○ Disagree
- ○ Slightly Disagree

Q10. I am willing to engage with my congress person for following issues.

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Theme 4: Involvement

The involvement theme is expected to help understand the participant's involvement to act in solving various mentioned issues. Please indicate if you take action in resolving the issues below.

Q11. I currently take specific action to make my community more sustainable with respect to achieving following goals.

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○

	Strongly agree	agree	Slightly agree	disagree	Strongly disagree
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Validation Check: What is 4+2?

Theme 5: Perception

The perception theme is intended to understand the participant's perception about solving the issues. Please indicate how optimistic you are in solving the mentioned issues are for your city.

Q12. How optimistic are you that the issues will improve?

	Extremely optimistic	Optimistic	Slightly optimistic	pessimistic	Extremely pessimistic
Poverty	○	○	○	○	○
Hunger	○	○	○	○	○

	Extremely optimistic	Optimistic	Slightly optimistic	pessimistic	Extremely pessimistic
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Theme 6: Behavior

The behavior theme is intended to understand the participant's behavioral pattern about solving the issues. Please indicate how likely would you take action in resolving the issues below.

Q13. I currently conserve the use of electric energy at my home.

○ Strongly Agree
○ Agree
○ Slightly Agree
○ Disagree

- ○ Strongly Disagree

Q14. I want to help make my community be more sustainable.

- ○ Strongly Agree
- ○ Agree
- ○ Slightly agree
- ○ Disagree
- ○ Strongly Disagree

Q15. I would like to conserve the use of electric energy at my house.

- ○ Strongly Agree
- ○ Agree
- ○ Slightly agree
- ○ Disagree
- ○ Strongly Disagree

Q16. The following SDGs will be achieved within 10 years in your community.

	Strongly agree	Agree	Neutral	disagree	Strongly disagree
Poverty	○	○	○	○	○

	Strongly agree	Agree	Neutral	disagree	Strongly disagree
Hunger	○	○	○	○	○
Health and well - being	○	○	○	○	○
Education	○	○	○	○	○
Water and sanitation	○	○	○	○	○
Affordable and clean energy	○	○	○	○	○
Decent work and economic growth	○	○	○	○	○

Theme 6: Demographics

Next, we will collect some demographic information. Note that preferring to not disclose is an option for every item.

Q17. State you live in.

Q18. City you live in

Q19. Zip code of the place you live in

Q20. Highest Education Level Completed

- High school
- Bachelors
- Community College/Trade School
- Graduate
- Postgraduate and above
- Other
- Decline to state

Q21. Please tell us your age

Q22. Occupation

Q23. Gender

- Male
- Female
- Non-binary
- Decline to state

Q24.Sexuality

- Asexual
- Bisexual
- Gay
- Heterosexual or Straight
- Lesbian
- Pansexual
- Queer
- None of the above, please specify

Q25. Political affiliation

- Very conservative
- somewhat conservative/right leaning
- middle of the road
- somewhat liberal/left leaning
- very liberal/progressive

Q26. Race

- American Indian or Alaska Native
- Asian
- Black or African American
- Native Hawaiian or Other Pacific Islander
- White
- more than one race/ethnicity

Q27. Income Level of the individual

- <25,000
- 25,000-49,999
- 50,000-69,999
- 75,000-99,999
- >100,000

Q28. How did you find out about the survey?

Thank you for your time.

Here is your Mechanical Turk Code:

SMSC-${e://Field/MechanicalTurkID}-AU

Sorry for the inconvenience. We won't be able to take your response for this survey.

GEE Code

```
/**
 * Function to mask clouds based on the pixel_qa band of Landsat SR data.
 * @param {ee.Image} image Input Landsat SR image
 * @return {ee.Image} Cloudmasked Landsat image
 */
var cloudMaskL457 = function(image) {
  var qa = image.select('pixel_qa');
  // If the cloud bit (5) is set and the cloud confidence (7) is high
  // or the cloud shadow bit is set (3), then it's a bad pixel.
  var cloud = qa.bitwiseAnd(1 << 5)
                .and(qa.bitwiseAnd(1 << 7))
                .or(qa.bitwiseAnd(1 << 3));
  // Remove edge pixels that don't occur in all bands
  var mask2 = image.mask().reduce(ee.Reducer.min());
  return image.updateMask(cloud.not()).updateMask(mask2);
};


var dataset = ee.ImageCollection('LANDSAT/LT05/C01/T1_SR')
                .filterDate('1990-01-01', '1990-12-31')
               .map(cloudMaskL457);

/** to clip the images to the geometry ***/

dataset = dataset.map(function(img){return img.clip(geometry)});

var composite = dataset.median();

var visParams = {
  bands: ['B4', 'B3', 'B2'],
  min: 0,
  max: 3000,
  gamma: 1.4,
};
Map.setCenter(-86, 33.2513, 8);

var gcps = urban.merge(barren).merge(water).merge(vegetation);

var addIndices = function(image) {
  var ndvi = image.normalizedDifference(['B4', 'B3']).rename(['ndvi']);
  var ndbi = image.normalizedDifference(['B5', 'B4']).rename(['ndbi']);
  var mndwi = image.normalizedDifference(['B2', 'B5']).rename(['mndwi']);
  var bsi = image.expression(
      '(( X + Y ) - (A + B)) /(( X + Y ) + (A + B)) ', {
```

```
    'X': image.select('B5'), //swir1
    'Y': image.select('B3'),  //red
    'A': image.select('B4'), // nir
    'B': image.select('B1'), // blue
  }).rename('bsi');
  return image.addBands(ndvi).addBands(ndbi).addBands(mndwi).addBands(bsi)
}

var composite = addIndices(composite);

var visParams = {bands: ['B4', 'B3', 'B2'], min: 0, max: 3000, gamma: 1.2};


// Normalize the image

function normalize(image){
  var bandNames = image.bandNames();
  // Compute min and max of the image
  var minDict = image.reduceRegion({
    reducer: ee.Reducer.min(),
    geometry: geometry,
    scale: 20,
    maxPixels: 1e9,
    bestEffort: true,
    tileScale: 16
  });
  var maxDict = image.reduceRegion({
    reducer: ee.Reducer.max(),
    geometry: geometry,
    scale: 20,
    maxPixels: 1e9,
    bestEffort: true,
    tileScale: 16
  });
  var mins = ee.Image.constant(minDict.values(bandNames));
  var maxs = ee.Image.constant(maxDict.values(bandNames));

  var normalized = image.subtract(mins).divide(maxs.subtract(mins))
  return normalized
}

var composite = normalize(composite);
// Add a random column and split the GCPs into training and validation set
var gcp = gcps.randomColumn()

var trainingGcp = gcp.filter(ee.Filter.lt('random', 0.6));
```

```
var validationGcp = gcp.filter(ee.Filter.gte('random', 0.6));
// Overlay the point on the image to get training data.
var training = composite.sampleRegions({
  collection: trainingGcp,
  properties: ['landcover'],
  scale: 10,
  tileScale: 16
});
// Train a classifier.
var classifier = ee.Classifier.smileRandomForest(50)
.train({
  features: training,
  classProperty: 'landcover',
  inputProperties: composite.bandNames()
});

// Classify the image.
var classified = composite.classify(classifier);

//**************************************************************************
// Accuracy Assessment
//**************************************************************************

// Use classification map to assess accuracy using the validation fraction
// of the overall training set created above.
/*var test = classified.sampleRegions({
  collection: validationGcp,
  properties: ['landcover'],
  scale: 10,
  tileScale: 16
});

var testConfusionMatrix = test.errorMatrix('landcover', 'classification')
// Printing of confusion matrix may time out. Alternatively, you can export it as CSV
print('Confusion Matrix', testConfusionMatrix);
print('Test Accuracy', testConfusionMatrix.accuracy());

**/
//**************************************************************************
// Exporting Results
//**************************************************************************
var citylimits = ee.FeatureCollection('users/MeghaShrestha/citylimits');
citylimits = citylimits.geometry();

Export.image.toDrive({
  image: classified,
```

```
  description: 'LULC1990',
  folder: 'LULC',
  region: citylimits,
  scale: 30,
  crs: 'EPSG:3395'
});

/***Export.image.toDrive({
  image: classified,
  description: 'LULC1990',
  folder: 'LULC',
  region: huntsville,
  scale: 30,
  crs: 'EPSG:3395'
});**/
```

RS code

```
library(lavaan)
responses <- read.csv('surveydata_cfa.csv')
responses[5:96] <- lapply(responses[5:96], as.numeric)
responses[97] <- lapply(responses[97], as.character)
responses[100] <- lapply(responses[100], as.character)
responses[102] <- lapply(responses[102], as.character)
responses[104:105] <- lapply(responses[104:105], as.character)
responses[107:109] <- lapply(responses[107:109], as.character)

no_typos <- responses

#making labels for demographics data

no_typos$Gender <- factor(no_typos$Gender,
                    levels = c("1","2","3","4"),
                    labels = c("0", "1","Non-binary", "Decline to State"))

no_typos$State <- factor(no_typos$State,
                   levels = c("4","56","61","62","69","70","72","76","85","92","94","98","100"),
                   labels = c("Alabama",
"Arkansas","Florida","Georgia","Kentucky","Louisiana","Maryland","Mississippi","North
Carolina","South Carolina","Tennessee","Virginia","West Virginia"))

no_typos$Education <- factor(no_typos$Education,
                      levels = c("1","2","3","4", "5","6","7"),
                      labels = c("High School", "Bachelors", "Community College/Trade School",
                             "Graduate", "Postgraduate and above", "Other", "Decline to state"))
```

```
no_typos$Sexuality <- factor(no_typos$Sexuality,
                        levels = c("1","2","3","4","5","6","7","8"),
                        labels = c("Asexual", "Bisexual","Gay", "Heterosexual",
                                 "Lesbian", "Pansexual","Queer","None of the above"))

no_typos$Political_affiliation <- factor(no_typos$Political_affiliation,
                                  levels = c("1","2","3","4","5"),
                                  labels = c("0", "0",
                                           "99", "1", "1"))
no_typos$Race <- factor(no_typos$Race,
                    levels = c("1","2","3","4","5","6"),
                    labels = c("American Indian or Alaska Native", "Asian","Black or African
American",
                             "Native Hawaiian or Other Pacific Inslander",
                             "White", "More than one race/ethnicity"))

no_typos$Income_level <- factor(no_typos$Income_level,
                          levels = c("1","2","3","4","5"),
                          labels = c("0", "0","1", "1","1"))
no_missing <- no_typos

obVar <- no_typos[5:109]

no_outliers <- obVar

no_outliers_g<-subset(no_outliers, Gender!="Non-binary" & Gender!="Decline to State")
no_outliers_p<-subset(no_outliers, Political_affiliation!="99")

#CFA model
mgmodel <- '
awarenessandfamilarity =~ AW1 + AW2 + AW3a + AW3b + AW3c + AW3d + AW3e+ AW3f+
AW3g+ AW3h+ AW3i+ AW3j+ AW3k + AW3l+ AW3m+ AW3n+ AW3o+ AW3p+ AW3q
concernUrgency =~ CU1a + CU1b + CU1c + CU1d + CU1e + CU1f+ CU1g+ CU1h+ CU1i+
CU1j+ CU1k+ CU1l+ CU1m+ CU2a + CU2b+ CU2c+ CU2d+ CU2e+ CU2f+ CU2g + CU3a+
CU3b+ CU3c+ CU3d+ CU3e+ CU3f+ CU3g+ CU4a + CU4b+ CU4c+ CU4d+ CU4e+ CU4f+
CU4g
intendedBehavior =~ IB_E1a + IB_E1b + IB_E1c + IB_E1d + IB_E1e + IB_E1f + IB_E1g+
IB_E2 + IB_E3a + IB_E3b+ IB_E3c+ IB_E3d + IB_E3e + IB_E3f + IB_E3g
involvement =~ I1a + I1b + I1c + I1d + I1e + I1f + I1g
perception =~ P1a + P1b + P1c + P1d + P1e + P1f + P1g

'
#gender CFA model
baseline <- measEq.syntax(configural.model = mgmodel,
                    data = no_outliers_g,
                    ordered = TRUE,
```

```
                    parameterization = "delta",
                    ID.fac = "std.lv",
                    ID.cat = "Wu.Estabrook.2016",
                    group = "Gender",
                    group.equal = "configural")
model.baseline <- as.character(baseline)
fit.baseline <- cfa(model.baseline,
                data = no_outliers_g,
                group = "Gender",
                ordered = TRUE)
l<-lavCor(fit.baseline, ordered = TRUE, group = "Gender", output = "cor")
write.csv(l,"correlation_gender.csv")

write(paste(utils::capture.output(summary(fit.baseline, fit.measures = TRUE, standardized =
TRUE)),
     collapse = "\n"), file = "fit_conf_gam_mod.txt")
all.results<-matrix(NA, nrow = 3, ncol = 6)

all.results[1,]<-round(data.matrix(fitmeasures(fit.baseline, fit.measures = c("chisq.scaled",
"df.scaled","pvalue.scaled","rmsea.scaled","cfi.scaled","tli.scaled"))), digits=3)

prop4 <- measEq.syntax(configural.model = mgmodel,
                 data = no_outliers_g,
                 ordered = TRUE,parameterization = "delta",
                 ID.fac = "std.lv",
                 ID.cat = "Wu.Estabrook.2016",
                 group = "Gender",
                 group.equal = c("thresholds"))
model.prop4 <- as.character(prop4)
#Fitting thresholds invariance model in lavaan via cfa function
fit.prop4 <- cfa(model.prop4,
              data = no_outliers_g,
              group = "Gender",
              ordered = TRUE)
# Obtaining results from thresholds invariance model
write(paste(utils::capture.output(summary(fit.prop4, fit.measures = TRUE, standardized =
TRUE)),
     collapse = "\n"), file = "fit_thres_gam_mod.txt")

#Extracting fit indices into the second row of all.results matrix
all.results[2,]<- round(data.matrix(fitmeasures(fit.prop4,fit.measures =
c("chisq.scaled","df.scaled","pvalue.scaled","rmsea.scaled","cfi.scaled","tli.scaled"))),digits=3)
l<-lavTestLRT(fit.baseline,fit.prop4)
write.csv(l,"thresholdg_mod.csv")
```

```
lats <- lavTestScore(fit.prop4)
write.csv(lats,"lats_g_metricam_mod.csv")

pm <- parTable(fit.prop4)
write.csv(pm, "pm_metricinvar_gam_mod.csv")

prop7 <- measEq.syntax(configural.model = mgmodel,
                       data = no_outliers_g,
                       ordered = TRUE,
                       parameterization = "delta",
                       ID.fac = "std.lv",
                       ID.cat = "Wu.Estabrook.2016",
                       group = "Gender",
                       group.equal = c("thresholds", "loadings"),
                       group.partial = c("concernUrgency=~CU1d","intendedBehavior =~ IB_E2",
                                         "CU1d | t1"))
model.prop7 <- as.character(prop7)
fit.prop7 <- cfa(model.prop7,
                 data = no_outliers_g,
                 group = "Gender",
                 ordered = TRUE,
)
write(paste(utils::capture.output(summary(fit.prop7, fit.measures = TRUE, standardized =
TRUE)),
             collapse = "\n"), file = "fit_thresload_gam_mod.txt")
all.results[3,] <- round(data.matrix(fitmeasures(fit.prop7, fit.measures = c("chisq.scaled",
"df.scaled", "pvalue.scaled", "rmsea.scaled", "cfi.scaled", "tli.scaled"))), digits = 3)
write.csv(all.results,"all_resultsg_mod.csv")
l<-lavTestLRT(fit.prop4,fit.prop7)
write.csv(l,"threshold_loadg_mod.csv")


lats <- lavTestScore(fit.prop7)
write.csv(lats,"lats_g_scalaram_mod.csv")

pm <- parTable(fit.prop7)
write.csv(pm, "pm_scalarinvar_gam_mod.csv")

#income
baseline <- measEq.syntax(configural.model = mgmodel,
                          data = no_outliers,
                          ordered = TRUE,
                          parameterization = "delta",
                          ID.fac = "std.lv",
                          ID.cat = "Wu.Estabrook.2016",
                          group = "Income_level",
```

```
                    group.equal = "configural")
model.baseline <- as.character(baseline)
fit.baseline <- cfa(model.baseline,
                data = no_outliers,
                group = "Income_level",
                ordered = TRUE)

write(paste(utils::capture.output(summary(fit.baseline, fit.measures = TRUE, standardized =
TRUE)),
         collapse = "\n"), file = "fit_conf_inam12.txt")

l<-lavCor(fit.baseline, ordered = TRUE, group = "Income_level", output = "cor")
write.csv(l,"correlation_income.csv")

all.results<-matrix(NA, nrow = 3, ncol = 6)

all.results[1,]<-round(data.matrix(fitmeasures(fit.baseline, fit.measures = c("chisq.scaled",
"df.scaled","pvalue.scaled","rmsea.scaled","cfi.scaled","tli.scaled"))), digits=3)

prop4 <- measEq.syntax(configural.model = mgmodel,
                  data = no_outliers,
                  ordered = TRUE,parameterization = "delta",
                  ID.fac = "std.lv",
                  ID.cat = "Wu.Estabrook.2016",
                  group = "Income_level",
                  group.equal = c("thresholds"))
model.prop4 <- as.character(prop4)
#Fitting thresholds invariance model in lavaan via cfa function
fit.prop4 <- cfa(model.prop4,
              data = no_outliers,
              group = "Income_level",
              ordered = TRUE)
# Obtaining results from thresholds invariance model
write(paste(utils::capture.output(summary(fit.prop4, fit.measures = TRUE, standardized =
TRUE)),
         collapse = "\n"), file = "fit_thres_inam12.txt")

#Extracting fit indices into the second row of all.results matrix
all.results[2,]<- round(data.matrix(fitmeasures(fit.prop4,fit.measures =
c("chisq.scaled","df.scaled","pvalue.scaled","rmsea.scaled","cfi.scaled","tli.scaled"))),digits=3)
l<-lavTestLRT(fit.baseline,fit.prop4)
write.csv(l,"threshold.csv")
prop7 <- measEq.syntax(configural.model = mgmodel,
                  data = no_outliers,
                  ordered = TRUE,
                  parameterization = "delta",
```

```
                    ID.fac = "std.lv",
                    ID.cat = "Wu.Estabrook.2016",
                    group = "Income_level",
                    group.equal = c("thresholds", "loadings"))
model.prop7 <- as.character(prop7)
fit.prop7 <- cfa(model.prop7,
               data = no_outliers,
               group = "Income_level",
               ordered = TRUE,
)
write(paste(utils::capture.output(summary(fit.prop7, fit.measures = TRUE, standardized =
TRUE)),
          collapse = "\n"), file = "fit_thresload_inam12.txt")
all.results[3,] <- round(data.matrix(fitmeasures(fit.prop7, fit.measures = c("chisq.scaled",
"df.scaled", "pvalue.scaled", "rmsea.scaled", "cfi.scaled", "tli.scaled"))), digits = 3)
write.csv(all.results,"all_results.csv")
l<-lavTestLRT(fit.prop4,fit.prop7)
write.csv(l,"threshold_load.csv")

#political affiliation
baseline <- measEq.syntax(configural.model = mgmodel,
                      data = no_outliers_p,
                      ordered = TRUE,
                      parameterization = "delta",
                      ID.fac = "std.lv",
                      ID.cat = "Wu.Estabrook.2016",
                      group = "Political_affiliation",
                      group.equal = "configural")
model.baseline <- as.character(baseline)
fit.baseline <- cfa(model.baseline,
                 data = no_outliers_p,
                 group = "Political_affiliation",
                 ordered = TRUE)

write(paste(utils::capture.output(summary(fit.baseline, fit.measures = TRUE, standardized =
TRUE)),
          collapse = "\n"), file = "fit_conf_pam12.txt")
all.results<-matrix(NA, nrow = 3, ncol = 6)

all.results[1,]<-round(data.matrix(fitmeasures(fit.baseline, fit.measures = c("chisq.scaled",
"df.scaled","pvalue.scaled","rmsea.scaled","cfi.scaled","tli.scaled"))), digits=3)

prop4 <- measEq.syntax(configural.model = mgmodel,
                    data = no_outliers_p,
                    ordered = TRUE,parameterization = "delta",
                    ID.fac = "std.lv",
```

```
                   ID.cat = "Wu.Estabrook.2016",
                   group = "Political_affiliation",
                   group.equal = c("thresholds"),
                   group.partial = c("I1e | t4","I1b | t4",
                                     "I1b | t1"))
model.prop4 <- as.character(prop4)
#Fitting thresholds invariance model in lavaan via cfa function
fit.prop4 <- cfa(model.prop4,
              data = no_outliers_p,
              group = "Political_affiliation",
              ordered = TRUE)
# Obtaining results from thresholds invariance model
write(paste(utils::capture.output(summary(fit.prop4, fit.measures = TRUE, standardized =
TRUE)),
          collapse = "\n"), file = "fit_thres_pam12.txt")

#Extracting fit indices into the second row of all.results matrix
all.results[2,]<- round(data.matrix(fitmeasures(fit.prop4,fit.measures =
c("chisq.scaled","df.scaled","pvalue.scaled","rmsea.scaled","cfi.scaled","tli.scaled"))),digits=3)
l<-lavTestLRT(fit.baseline,fit.prop4)
write.csv(l,"thresholdp.csv")

lats <- lavTestScore(fit.prop4)
write.csv(lats,"lats_p_metricam.csv")

pm <- parTable(fit.prop4)
write.csv(pm, "pm_metricinvar_pam.csv")

prop7 <- measEq.syntax(configural.model = mgmodel,
                   data = no_outliers_p,
                   ordered = TRUE,
                   parameterization = "delta",
                   ID.fac = "std.lv",
                   ID.cat = "Wu.Estabrook.2016",
                   group = "Political_affiliation",
                   group.equal = c("thresholds", "loadings"),
                   group.partial = c("I1e | t4","I1b | t4",
                                     "I1b | t1"))
model.prop7 <- as.character(prop7)
fit.prop7 <- cfa(model.prop7,
              data = no_outliers_p,
              group = "Political_affiliation",
              ordered = TRUE,
)
write(paste(utils::capture.output(summary(fit.prop7, fit.measures = TRUE, standardized =
TRUE)),
```

```
        collapse = "\n"), file = "fit_thresload_pam12.txt")
all.results[3,] <- round(data.matrix(fitmeasures(fit.prop7, fit.measures = c("chisq.scaled",
"df.scaled", "pvalue.scaled", "rmsea.scaled", "cfi.scaled", "tli.scaled"))), digits = 3)
write.csv(all.results,"all_resultsp.csv")
l<-lavTestLRT(fit.prop4,fit.prop7)
write.csv(l,"threshold_loadp.csv")

lats <- lavTestScore(fit.prop7)
write.csv(lats,"lats_p_scalaram.csv")

pm <- parTable(fit.prop7)
write.csv(pm, "pm_scalarinvar_pam.csv")

#sem model
sem_mgmodel1 <- '
awarenessandfamilarity =~ AW1 + AW2 + AW3a + AW3b + AW3c + AW3d + AW3e+ AW3f+
AW3g+ AW3h+ AW3i+ AW3j+ AW3k + AW3l+ AW3m+ AW3n+ AW3o+ AW3p+ AW3q
concernUrgency =~ CU1a + CU1b + CU1c + CU1d + CU1e + CU1f+ CU1g+ CU1h+ CU1i+
CU1j+ CU1k+ CU1l+ CU1m+ CU2a + CU2b+ CU2c+ CU2d+ CU2e+ CU2f+ CU2g + CU3a+
CU3b+ CU3c+ CU3d+ CU3e+ CU3f+ CU3g+ CU4a + CU4b+ CU4c+ CU4d+ CU4e+ CU4f+
CU4g
intendedBehavior =~ IB_E1a + IB_E1b + IB_E1c + IB_E1d + IB_E1e + IB_E1f + IB_E1g+
IB_E2 + IB_E3a + IB_E3b+ IB_E3c+ IB_E3d + IB_E3e + IB_E3f + IB_E3g
involvement =~ I1a + I1b + I1c + I1d + I1e + I1f + I1g
perception =~ P1a + P1b + P1c + P1d + P1e + P1f + P1g
behavior =~ B1 + B2 + B3

#regressions
involvement ~concernUrgency+awarenessandfamilarity
behavior ~ involvement+awarenessandfamilarity
intendedBehavior ~ involvement+perception


AW1 ~~  AW2
IB_E1a ~~ IB_E1b
CU3g ~~   CU4g
CU1l ~~   CU1m
AW3e ~~   AW3f
CU2a ~~   CU2b
intendedBehavior ~~ involvement
'

composite6.fit <- sem(model = sem_mgmodel1,
             #sample.cov = allcov,
             data = no_outliers,
             ordered = TRUE)
```

```
summary(composite6.fit, fit.measures = TRUE, standardized = TRUE)

#sem mediation model
sem_mediation <- '
awarenessandfamilarity =~ AW1 + AW2 + AW3a + AW3b + AW3c + AW3d + AW3e+ AW3f+
AW3g+ AW3h+ AW3i+ AW3j+ AW3k + AW3l+ AW3m+ AW3n+ AW3o+ AW3p+ AW3q
concernUrgency =~ CU1a + CU1b + CU1c + CU1d + CU1e + CU1f+ CU1g+ CU1h+ CU1i+
CU1j+ CU1k+ CU1l+ CU1m+ CU2a + CU2b+ CU2c+ CU2d+ CU2e+ CU2f+ CU2g + CU3a+
CU3b+ CU3c+ CU3d+ CU3e+ CU3f+ CU3g+ CU4a + CU4b+ CU4c+ CU4d+ CU4e+ CU4f+
CU4g
intendedBehavior =~ IB_E1a + IB_E1b + IB_E1c + IB_E1d + IB_E1e + IB_E1f + IB_E1g+
IB_E2 + IB_E3a + IB_E3b+ IB_E3c+ IB_E3d + IB_E3e + IB_E3f + IB_E3g
involvement =~ I1a + I1b + I1c + I1d + I1e + I1f + I1g
perception =~ P1a + P1b + P1c + P1d + P1e + P1f + P1g
behavior =~ B1 + B2 + B3

#regressions
involvement ~b1*concernUrgency+b3*awarenessandfamilarity
perception ~ b2*concernUrgency+b4*awarenessandfamilarity
behavior ~ b9*involvement+b6*awarenessandfamilarity+b5*concernUrgency
intendedBehavior ~
b7*concernUrgency+b10*perception+b11*involvement+b8*awarenessandfamilarity


AW1 ~~  AW2
IB_E1a ~~ IB_E1b
CU3g ~~   CU4g
CU1l ~~   CU1m
AW3e ~~   AW3f
CU2a ~~   CU2b

#indirect effects
b1b11 := b1*b11
b2b10 := b2*b10
#for intendedbehavior
#indirect CU
totalind_elCU := b1*b11+b2*b10
b3b11 := b3*b11
b4b10 := b4*b10
#indirect AW
totalind_AW := b3*b11+b4*b10
# Total effects
#total cU
total_elternCU := b1*b11+b2*b10 + b7
#total AW
total_freundeAW := b3*b11+b4*b10 + b8
```

```
#for behavior
b1b9 := b1*b9
b3b9 := b3*b9
#total CU
total_c := b1*b9 +b5
#total AW
total_a := b3*b9 +b6

'
mediation.fit <- sem(model = sem_mediation,
                 #sample.cov = allcov,
                 data = no_outliers,
                 ordered = TRUE,  se="bootstrap",
                 test="scaled.shifted",
                 estimator="DWLS", verbose=TRUE)
semmediation_indices <- fitMeasures(mediation.fit ,fit.measures = 'all')
write.csv(semmediation_indices ,"semmediation_indices.csv")
write(paste(utils::capture.output(summary(mediation.fit,fit.measures = TRUE, standardized = TRUE)),
          collapse = "\n"), file = "semmediation_indicesfull11.txt")
```

Website link: https://meghastha.github.io/AuburnSite/