DEEP LEARNING AND GEOSPATIAL ANALYSIS TO LOCATE MOBILE HOME PARKS AND ASSESS SOCIAL IMPACTS OF TORNADOES ON VULNERABLE COMMUNITIES

by

Kayleigh Taillefer

(Under the Direction of Marguerite Madden)

ABSTRACT: Mobile homes are an affordable housing option for many Americans, however the infrastructure of these homes make these communities more susceptible to harm from tornados. In this research, geographic information science (GIScience) and geospatial artificial intelligence (GeoAI) analysis were used to determine if deep learning algorithms can recognize mobile home parks from aerial imagery covering six counties in Georgia. A multi criteria decision analysis (MCDA) was also performed to assess the social impacts of tornados on vulnerable populations in Georgia. Data layers of mobile home parks, proximity to previous tornado tracks and socio-economic characteristics including race and income from the U.S. Census were combined to examine the disproportional social impact of tornadoes on residents of mobile home parks. The methodology developed in this research will allow local planners and disaster responders to identify and recognize local areas with vulnerable populations requiring disaster preparedness, response and recovery due to damaging tornados.

INDEX WORDS: Deep Learning, Multi Criteria Decision Analysis, Mobile Home Parks, Severe Weather, Tornados

DEEP LEARNING AND GEOSPATIAL ANALYSIS TO LOCATE MOBILE HOME PARKS AND ASSESS SOCIAL IMPACTS OF TORNADOES ON VULNERABLE COMMUNITIES

By

Kayleigh Taillefer

B.S., The University of Georgia, 2017

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2024

DEEP LEARNING AND GEOSPATIAL ANALYSIS TO LOCATE MOBILE HOME PARKS AND ASSESS SOCIAL IMPACTS OF TORNADOES ON VULNERABLE COMMUNITIES

By

Kayleigh Taillefer

Major Professor: Marguerite Madden

Committee: Lan Mu

Jennifer Rice

Ron Walcott

Dean of the Graduate School

The University of Georgia

December 2024

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to Dr. Marguerite Madden, my wonderful major professor. Her feedback and support mean the world to me. Additionally, I would like to thank my committee, Dr. Lan Mu and Dr. Jennifer Rice, both of whom have inspired me with their studies. I would not have completed my thesis without the help and support of my committee.

I want to thank my mom for being there for me and always picking up the phone no matter what time it is. Thank you, Jessica for being so supportive and cheering me up whenever I am down. Thank you, Abby for being such an amazing roommate and friend. Thank you, Sierra for being wonderful and inspiring me to move to Kansas City. Thank you Andreea for being a delight and there to talk about whatever. Thank you, Liza for being so kind and caring. Thank you, Maya and Kyle for being great friends throughout graduate school. Finally, thank you to my friends around the world for the constant support and encouragement.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND BACKGROUND

When one thinks of university towns such as Athens, Georgia, home of the University of Georgia, school spirit and college life often come to mind. However, there are other aspects to Athens and its surroundings that require attention. Families also reside there, and with increasing housing costs, many are struggling to find homes amongst the plethora of highly priced student housing and exorbitantly priced single-family homes. This leaves many with their only option being the purchase or rental of a manufactured mobile home in a mobile home park. These parks provide affordable housing, especially to the elderly, families with young children and African American, Latinx and Native American households (Rumbach et al. 2023). In many cases, families remain in their mobile homes for years.

Mobile home parks come in all shapes and sizes, ranging from parks with over two hundred spots for mobile homes and accommodations such as pools and playgrounds, to smaller lots with only few mobile homes. Mobile home parks do tend to have one thing in common, and that is the size and shape of the mobile homes and their pattern of arrangement that is recognizable when viewed from above. In a remotely sensed image of high spatial resolution acquired from satellites, airplanes or uncrewed aerial systems (UASs) (also known as drones), the homes in a mobile home park are all a similar size and rectangular shape, usually arranged close together in rows. The pattern of uniform home size, shape and arrangement in mobile home parks should be recognizable to image object detection and classification algorithms within the geospatial artificial intelligence (GeoAI) domain. Developing a methodology for detecting mobile home parks, individual mobile homes and parks with recreational vehicles from current remotely sensed imagery of high spatial resolution is needed to ensure digital planning and disaster response databases are up-to-date. This is especially important because living in a mobile home park does come with risks, with one being severe weather.

Severe weather is something we all must face, however, those who live in mobile homes are much more vulnerable than those who live in apartments and single-family homes. The structure of mobile homes causes them to be at risk to weather events with mid- to high-speed winds and flooding. One of the most dangerous natural disasters a resident of a mobile home can face is a tornado. Even the lowest level of tornadoes can severely damage mobile homes and increase the risk of harm done to members of the mobile home community. In order for risk to be assessed, local governments and emergency responders must know where mobile home parks are located within their community. This is where remote sensing imagery and deep learning come in.

In this research, in order to identify mobile home parks via satellite or aerial imagery, a GeoAI deep learning algorithm in ArcGIS Pro was used to create training and validation samples and perform a supervised neural network classification that learns the spatial pattern of mobile homes in mobile home parks. While traditional pixel-based supervised and unsupervised classification techniques have long been used to identify features in the landscape, they mainly rely on the spectral reflectance (i.e., color) of features such as buildings, roads, grass clearings and trees/shrubs visible within imagery of high spatial resolution. They do not consider the regular arrangement of small rectangular structures that is required to identify mobile home parks. Small subsets of images known as image chips can be used to illustrate existing mobile home parks and develop training sets to detect other potential mobile home parks in the most recently acquired satellite or aerial images. This research uses deep learning instead of traditional image classification algorithms because although pixel-based classification results are adequate for identifying small buildings in high-resolution images, deep learning has the potential to more thoroughly identify objects of particular shape, size and arrangement, thereby more accurately mapping a unique residential area that is associated with a socially vulnerable population, namely, mobile home parks.

Furthermore, once the mobile home parks are identified, GIS analysis of data collected by the U.S. Census Bureau permits the characterization of populations tending to reside in mobile home parks and identify marginalized groups at risk to natural disasters. This research is important because marginalized communities are so often overlooked and dismissed as “trailer park trash”, when in reality they are just like any other community facing struggles. It is hoped that this research sheds a light on the abundance and distribution of mobile home parks and the struggles their residents face, while also determining whether deep learning in ArcGIS Pro is a technique that can be used to identify these parks for urban-rural planning, disaster relief and future research.

Study Area

The study area for the entire project is centered on Athens Clarke County, Georgia and its surrounding area, including Jackson, Madison, Oglethorpe, Oconee and Barrow counties (Figure 1). The total study area including all six counties is approximately 1,541 mi^2 in size. Located in the Piedmont region of Georgia between the Blue Ridge Mountains to the north and the Upper Coastal Plain to the south, this section of Georgia has a fluvial landscape with rolling hills, valleys, and many creeks, streams, and rivers. The area can be described as having “warm and humid weather” during the summer and about 120 days of precipitation during the year (NWS

2024). This study area also has a history of tornadoes, with 46 tornadoes passing through the study area since 1950 (FEMA 2022) (Figure 2). According to Homefacts (2024), Athens Clarke County is designated as a Moderate Risk area for tornadoes with the largest F3 tornado in the area occurring in 1973 that caused one death and 65 injuries. Table 1 and Figure 2 both illustrate the number of tornadoes within the study area since 1950.

Table 1 – The number of tornadoes by county since 1950 within the study area (NOAA 2023).

County	**Number of Tornadoes since 1950**
Clarke County	8
Barrow County	8
Jackson County	13
Madison County	12
Oglethorpe County	5
Oconee County	12

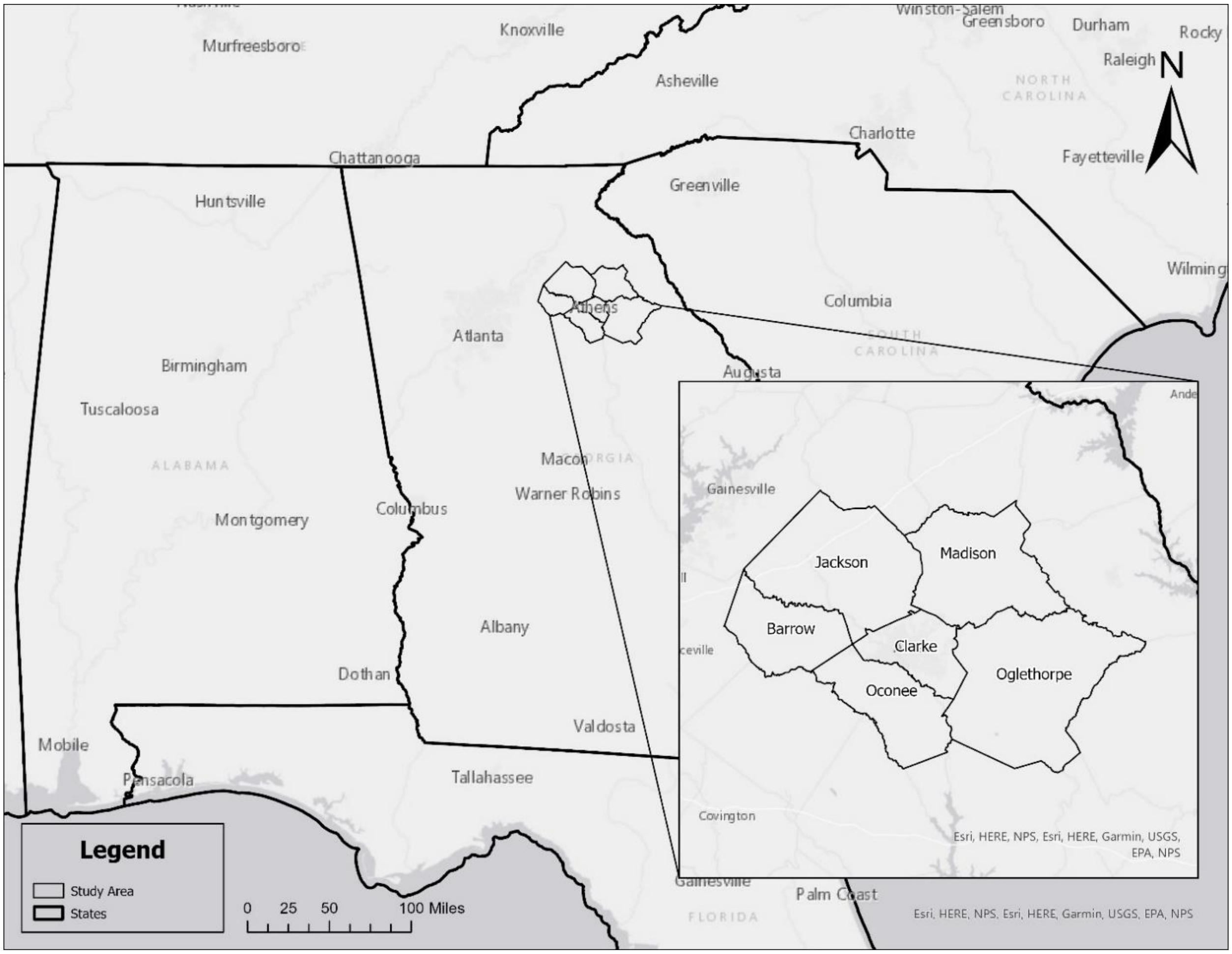


Figure 1- The southeastern United States with an inset map of the study area located in northeast Georgia.

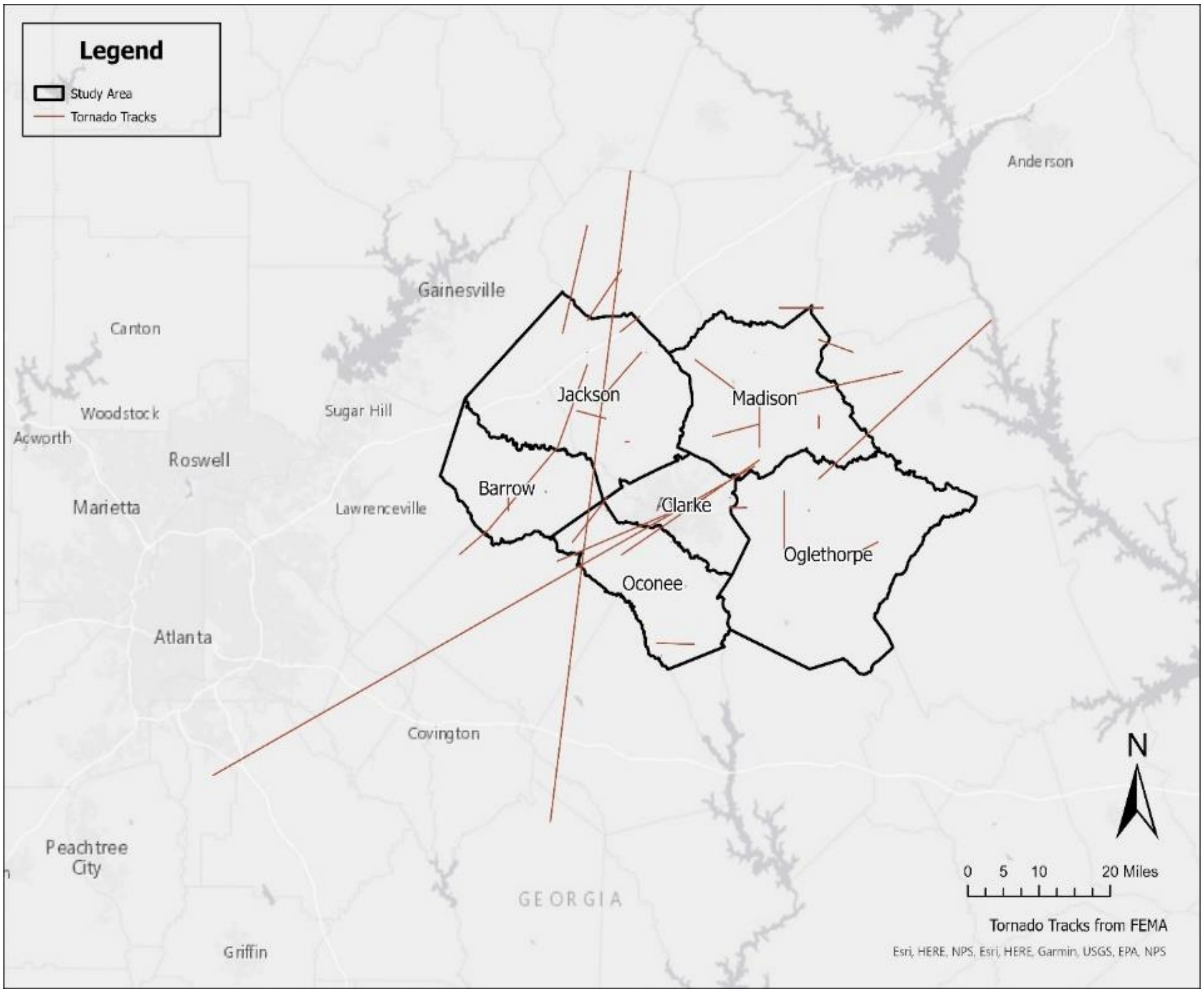
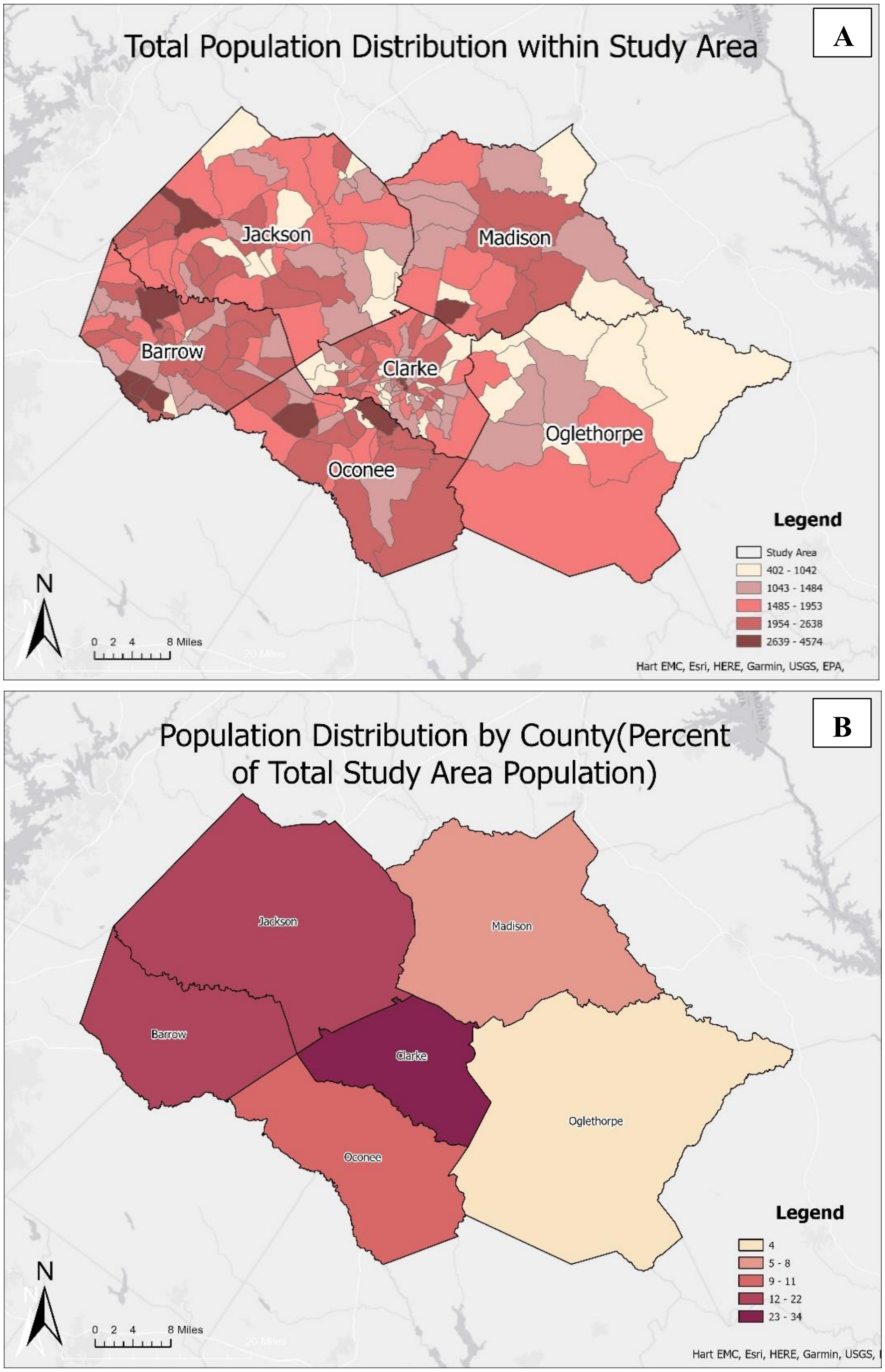


Figure 2 - Tornado tracks that have passed through the study area since 1950 (NOAA 2023).

Race and ethnicity have an infamous role in the history of housing in Athens and surrounding areas. Past redlining and housing discrimination have had a lasting impact on where people of various races and ethnicities reside today. Maps created using demographic data from the U.S. Census Bureau allow for a comparison of where residents of various races and ethnicities are located within the study area. Figure 3 depicts the 2020 population distribution by Census block groups within each county and Table 2 represents 2020 populations for each county. The Hispanic and/or Latinx populations (Figure 4) in the area are concentrated to the West of the study area in addition to a very high-density Northeast of downtown Athens, much like the Black population. It is most noticeable that there is a predominantly White population throughout the entire study area, with the highest proportion of White populations located in Oconee, Barrow, Jackson and Madison counties and the lowest in Oglethorpe county and Northeast Athens-Clarke County (Figure 5). In contrast, the largest Black population within the study area is primarily in the Northeast Athens-Clarke county area and Oglethorpe and Barrow counties (Figure 6). This is likely a residual impact of the past redlining in the area, especially in the areas Northeast of downtown Athens, as well as the integration of schools in the 1970s. The Black population in the rest of the study area is relatively low, with one of the block groups only having only three Black residents.

Table 2 - The population of the counties in the study area as of 2020 (Georgia General Assembly, 2021).

County	Population (2020)
Clarke	128,671
Barrow	83,505
Jackson	75,907
Madison	30,120
Oglethorpe	14,825
Oconee	47,799



.

Figure 3 –A) Total population by Census block group and B) percent population distribution by county of within the study area. Legend represents population size as of 2020 (IPUMS NHGIS 2020).

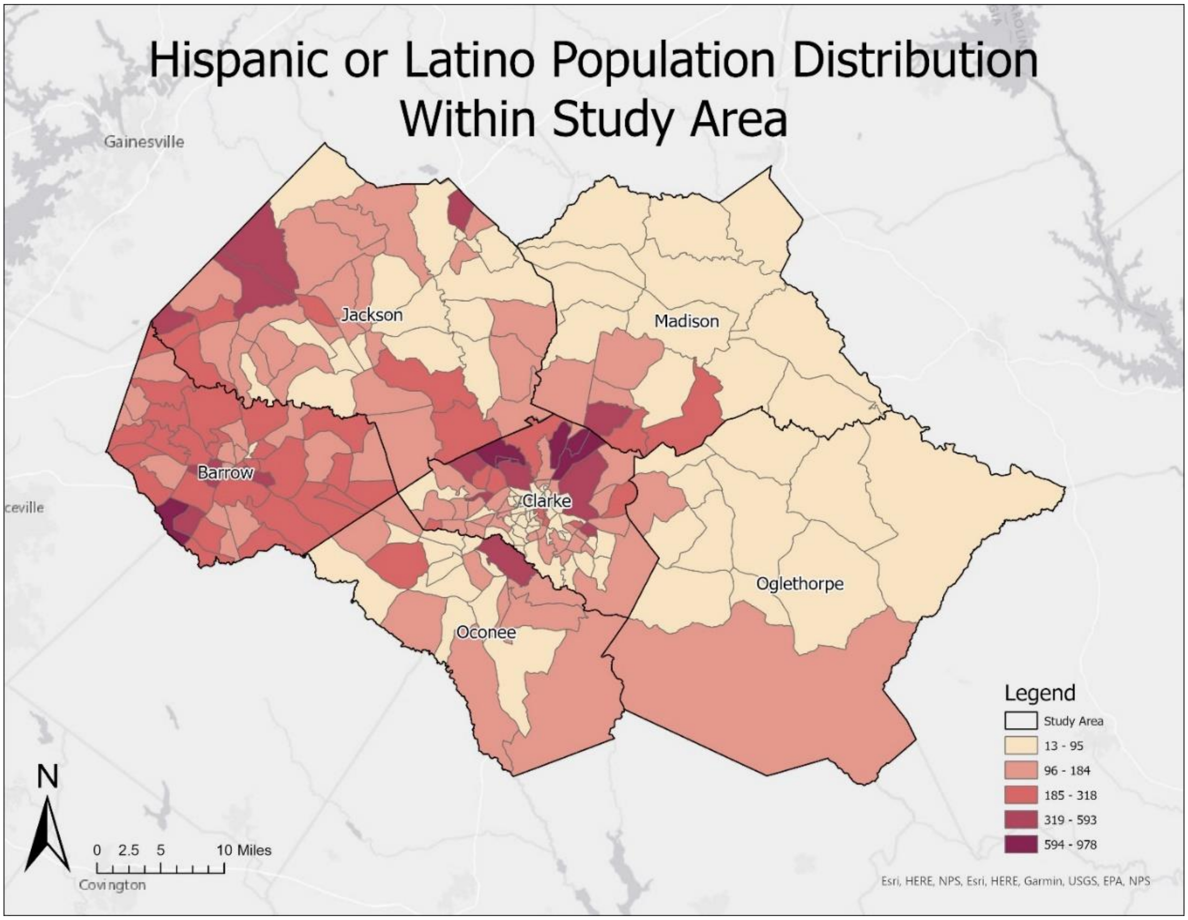


Figure 4 – Hispanic or Latinx Population by U.S. Census block group within the study area. Legend represents population as of 2020 (IPUMS NHGIS 2020).

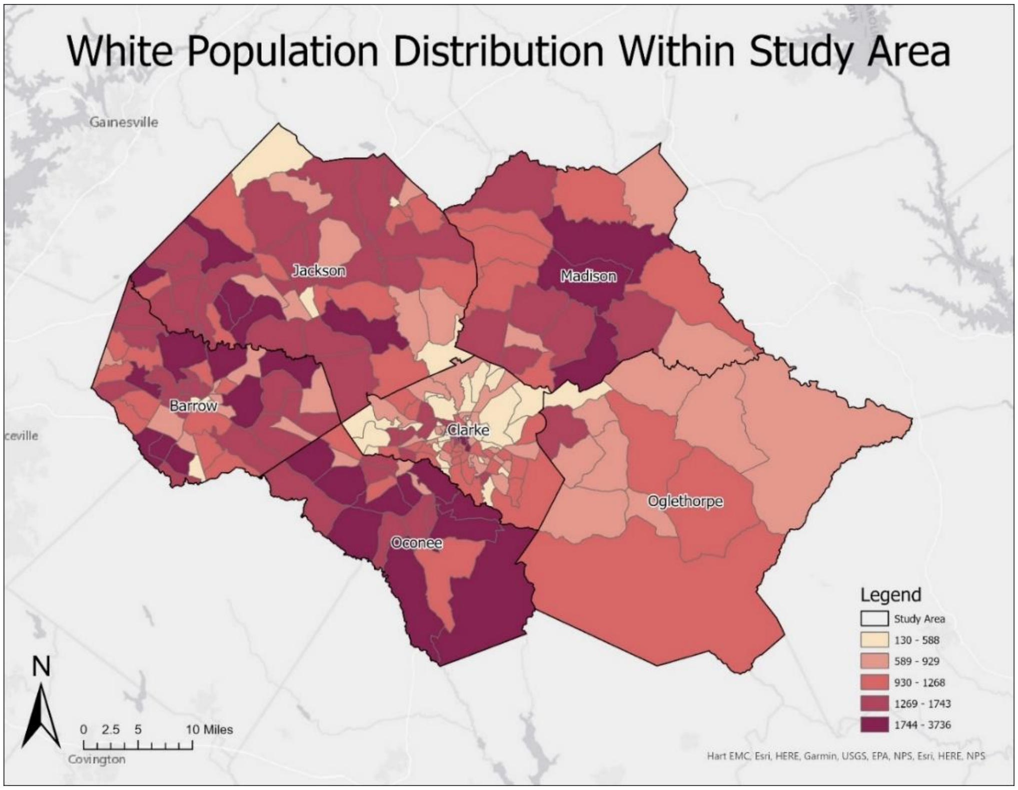


Figure 5- White population by U.S. Census block group within the study area. Legend represents population as of 2020 (IPUMS NHGIS 2020).

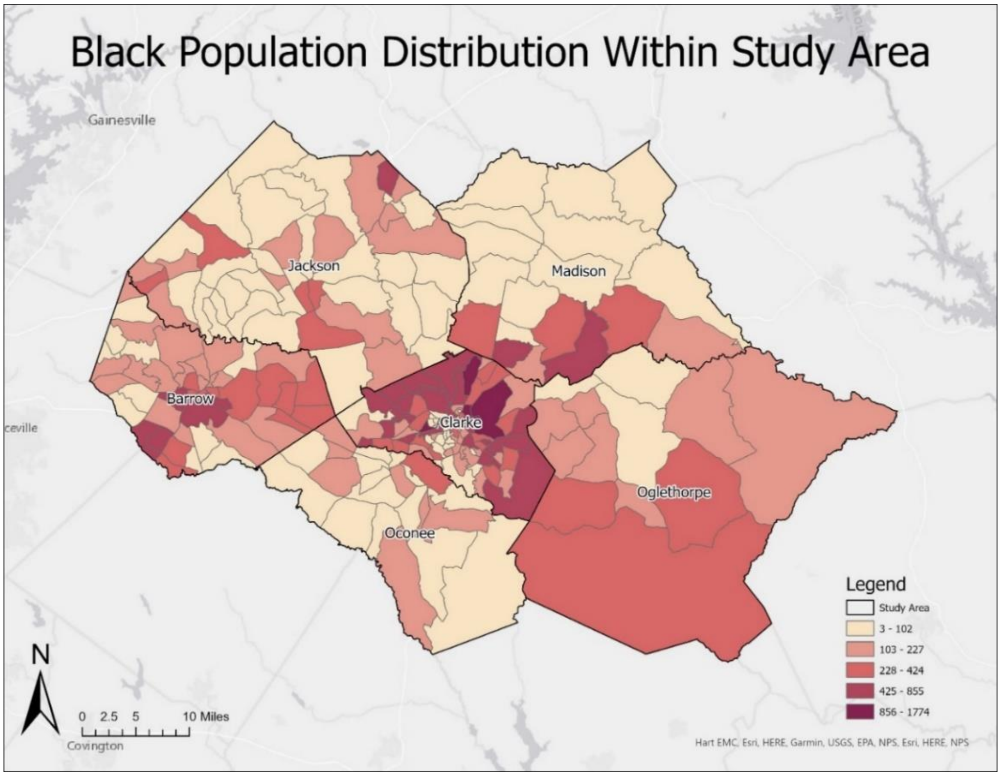


Figure 6- Black population distribution by U.S. Census block group within the study area. Legend represents Black population as of 2020 (IPUMS NHGIS 2020).

Research Questions

Although previous studies have used deep learning with high-resolution and satellite imagery, there is a lack of attention on the residents of mobile home parks who are especially vulnerable to natural disasters such as tornadoes. Therefore, my research addresses the following research questions:

1) Can deep learning be used to recognize mobile home parks?

2) Based on the tracks of past tornados in the study area, what percentage of mobile homes/mobile home parks would have been at high risk of being impacted?

3) Also based on the tracks of past tornados, what are the demographic characteristics of areas that have mobile homes/mobile home parks located within areas that would have been impacted by past tornados.

CHAPTER 2

LITERATURE REVIEW

As the housing market becomes more unaffordable, mobile homes offer a low-cost option for renting or owning a home. Some mobile home parks have features similar to neighborhoods, such as pools, tennis courts, and a sense of community with one's neighbors. The draw of mobile homes is mostly the cost, which is, "on average, half as much per square foot ($59.14) as site-built, single family homes ($122.12)" (Sullivan et al. 2021). This allows for low-income households, or even those wishing to save money on housing, an opportunity to own a home without the added cost of single-family homes. Mobile homes are not an uncommon residence. Approximately 18 million residents in the U.S. live in manufactured housing (Sullivan et al. 2021).

The residents of mobile homes can be generally characterized by race or economic status. Brooks and Mueller (2020) state, "the percentage of African Americans in a county had the strongest relationship with mobile home prevalence, wherein a percentage of African American residents relates to a higher prevalence of mobile homes". This is likely due to a history of redlining, from government maps that outlined areas deemed risky investments due to predominantly Black residents. The redline maps resulted in systemic prevention of African Americans from being approved for loans to purchase homes or start businesses as easily as White homeowners (Jackson 2021). Additionally, this demonstrates how marginalized communities are disproportionately impacted by severe weather. If a person of color is more likely to live in a mobile home, they are at greater risk of the impacts of severe weather than someone living in a single-family home. Additionally, economics plays a factor in who lives in mobile home parks and what counties are more likely to have an increased number of mobile home parks. Based on research done by Brooks and Mueller (2019), “one would expect high levels of mobile home percentages in small, but fast growing, not economically prosperous counties”. These researchers provide a few economic indicators such as areas that are growing quickly are more likely to have mobile home parks. This could be due to housing availability, or lack thereof. The housing market, as previously mentioned, often provides rents that are inaccessible to families, leaving them to find affordable housing elsewhere. High levels of mobile homes in counties with low economic growth can reveal financial struggles for those in the community, leading people to seek out more low-cost housing.

One would assume that with the enhanced vulnerability of people living in mobile home parks to severe weather, that the mobile home parks themselves would have shelters for residents to evacuate to in the event of a storm. However, fewer than 20% of mobile home parks or communities in the Southeast are estimated to provide storm shelters for their residents, while 75% or more of mobile home parks in the Central Plains have storm shelters (Strader, et al. 2019). This lack of safe infrastructure for mobile home residents means the residents have to struggle to find shelter at the last minute, or in the worst-case scenario, stay in their mobile homes during severe storms. Whether it is to cut costs for the mobile home park owner or simply due to a lack of space, not having a shelter on-site is an incredibly dangerous prospect for those who reside in mobile home parks given how vulnerable mobile homes are to wind damage, especially by tornadoes. Furthermore, with many mobile home parks containing marginalized communities, it is clear that residency in a mobile home park results in a higher risk of harm from severe weather, disproportionately impacting these marginalized communities.

Tornadoes are a complex phenomenon that occur frequently throughout the United States, but are focused more specifically on an area colloquially called “Tornado Alley” where conditions are typically most favorable for the formation of tornadoes. While Tornado Alley does not have a specific location, due to variance in tornado measurement techniques, it is most commonly represented as the central United States, extending east into areas such as Georgia and Tennessee (NOAA 2023). However, since 1989, the extent of Tornado Alley has shifted further eastward, leading to more tornadoes in the Southeast, especially in areas such as Georgia, Alabama and South Carolina (Fischetti et al. 2024). While areas of the Midwest are prepared to handle tornadoes, the Southeastern United States is not and leaves those in vulnerable communities, including mobile home parks, in a more dangerous position.

In 2007, the Enhanced Fujita Scale (EF Scale) was implemented to rate tornadoes based on estimated wind speed and damage. The EF scale allows those who study severe weather to track and record past and future tornadic activity (NWS 2024). Prior to this, there was the Fujita Scale, which focuses less on structural damage and more on wind speeds. The EF Scale has 28 damage indicators ranging from trees to automobile showrooms. Included in this list are single-wide mobile homes and double-wide mobile homes, represented by the abbreviations MHSW and MHDW, respectively (NWS 2024). These are included in the EF scale due to their vulnerability to high winds and tornadoes.

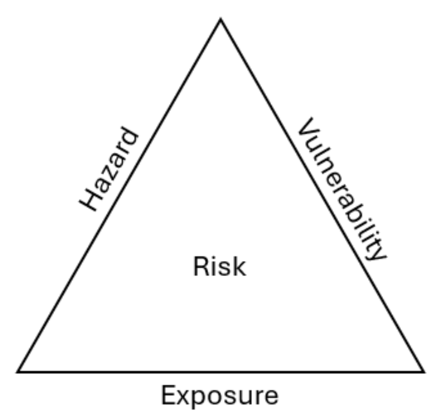


Figure 7- Risk triangle according to David Crichton. Hazard, vulnerability, and exposure make up the risk (Crichton 1999)

The Risk Assessment Triangle, created by David Crichton, provides important insight as to what factors come together to create Risk, namely, three elements of hazard, vulnerability, and exposure (Figure 7, Crichton 1999). Originally created for insurers and those working in disaster management, the three components can be broken down in order to assess risk from storms for specific communities. Hazard, as defined by the Risk Triangle, includes storms and flooding. In the case of the Triangle, "vulnerability" refers to cost of damage that insurers may have to pay. Due to the infrastructure of mobile homes being so fragile, this is a key factor in determining the dangers of living in a mobile home. While not originally intended as the definition of vulnerability, within the context of this research, it can refer to vulnerable communities as well. Vulnerable communities are generally considered to be anyone who has been systemically oppressed by the government and society. This includes, but is not limited to, people of color, low-income families, and immigrants. Finally, the idea of "exposure" completes the Triangle. This is defined by whether or not the given home or building is within a hazardous area (Crichton, 1999). The study area for this project is located within an area that has a moderate risk of tornadoes, meaning the exposure level would be moderate for residents living in the study area.

Challenges Mapping Mobile Home Parks with Remotely Sensed Imagery

Urban areas can be challenging to map based on satellite imagery alone. While some buildings may stand out or are recognizable, it can be difficult to identify varying types of infrastructure within a remotely sensed image without an abundance of ground truth knowledge, experience in interpreting aerial images or using an advanced image analysis technique such as

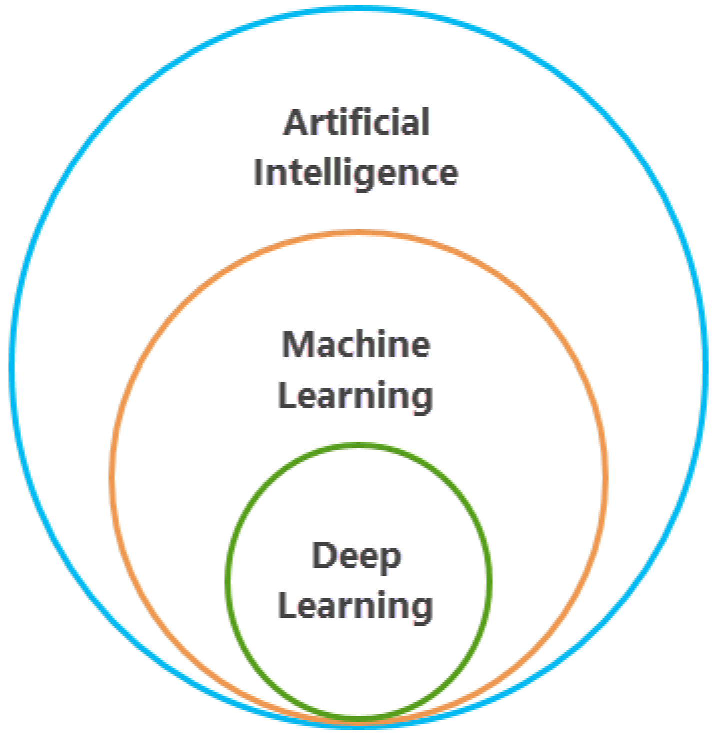


Figure 8- A diagram depicting how deep learning fits within machine learning and artificial intelligence (ESRI 2024).

deep learning. Deep learning is an emerging method of image analysis that provides a more in-depth means of geographic delineation and identification of features.

Deep learning falls under the umbrella of artificial intelligence, or AI, and is a subset of machine learning that uses layers of algorithms to “map” a set of input values to output values (Figure 8, Goodfellow et al. 2016, “Introduction to Deep Learning” 2024). The layers in the form of a neural network allow the user to train the algorithms to recognize patterns in data using a series of computer processes vs. identifying and classifying features manually (ESRI 2024). Deep learning solves the problem of extracting high-level features from raw data using an almost human-understanding of the data and building complex concepts from simpler representations (Goodfellow, et al. 2016). “Since 2014, deep learning algorithms in the field of remote sensing have significant successes, particularly for their ability to predict complex patterns, especially those related to image analysis, including land use and land cover (LULC) classification, scene classification, and object detection” which has allowed for a much more in-depth look at satellite imagery (Youssef, et al. 2020). This has created new opportunities for the future of remote sensing, image classification and advanced types of features deep learning can recognize (Cheng and Han 2016, Maggiori et al. 2017, Ienco et al. 2017, Cresson 2020).

In an article by Gon Cheng and Junwei Han, it is stated that higher quality satellite and airborne imagery allows for a greater detection of man-made objects which means that with better imagery, better remotely sensed detections through deep learning can be accomplished (Cheng and Han, 2016). Satellite and airborne imagery have become more accessible and at higher spatial resolutions. For example, 3.7-m Planet imagery is acquired by a constellation of nanosatellites and aerial National Agriculture Imagery Program (NAIP) imagery can be as high as 0.6-m resolution (USGS Eros Archive 2018, "LibGuides: Planet Labs Satellite Imagery" 2024). The increased detail provided by these image datasets, creates more applications for deep learning to accurately detect features in the landscape. The importance of deep learning in the field of geography cannot go unnoticed, as "deep learning has been successfully used for various visual recognition tasks such as classification of surface objects, objects detection and change detection in remote sensing images" (Huang, et al. 2019).

Object detection using deep learning provides a method for the assessment of high-resolution satellite and aerial imagery. "Object detection in optical remote sensing images (RSIs) is to determine if a given aerial or satellite image contains one or more objects belonging to the class of interest and locate the position of each predicted object in the image," which allows the user to identify objects of various size and shape within the image (Cheng and Han, 2016). With object detection, one has to be aware of the obstacles that could get in the way of object recognition. Often times, one has to account for things like foliage, similar shaped buildings or objects, and clouds. Furthermore, variations in the image viewpoint or angle of image acquisition, occlusions from trees or other buildings, background clutter, color/illumination and shadow can create issues within the deep learning environment that reduce object detection accuracy (Cheng and Han, 2016). These variations can distort the image or the objects within the image, making it harder for the deep learning software to properly recognize and identify the target object. The number, quality and nature of samples that are input to the deep learning algorithm can accommodate some of this variation. With the advancements in deep learning itself, this has been considered and worked on in order to make deep learning software more accurate for the average user. In an article published by Kin Sam Yen and Hui Liu, shadow detection and removal are discussed in order to improve accuracy in deep learning models for uses such as agriculture and traffic control (Yen and Liu, 2024). These improvements could be extrapolated for other areas of object detection including mobile homes.

When considering the use of deep learning to identify small structures in an urban setting, one must examine patterns and consistencies between images in terms of the features of interest. In a study done by Hadi Yazdi and colleagues, remote sensing was used to identify a specific type of Iranian architecture in order to identify central courtyards, which "are primary components of vernacular architecture in Iran" (Yazdi, et al. 2021). In the case of this courtyard project, the researchers determined their deep learning model "can predict and identify the optimal form of a central courtyard in a historic region based on thousands of courtyard samples" (Yazdi, et al. 2021). Courtyards being a consistent shape with specific features within the courtyards and surrounding buildings aided the deep learning model in recognizing other similar courtyards. This extrapolation of information is important when discussing deep learning, because with any science, it is important for it to be repeatable.

Aerial and satellite imagery and classification have been used to recognize relatively small human-built features in the landscape such as roof shapes and identifying dams (Castagno and Atkins 2018, Arnold 2023). In a study performed by Jeremy Castagno and Ella Atkins, Light Detection and Ranging (LiDAR) data and aerial imagery were used to classify various roof shapes using convolutional neural networks. As a result, "the generalized models and test datasets show promise for applying machine learning to automatically label roof shapes around the world with high confidence" (Castagno and Atkins 2018). With accuracies up to 98.3%, this study gives a strong indication that machine learning will also be able to recognize mobile home parks due to their consistent patterns and roof shapes. Furthermore, an additional study, "Locating Low Head Dams Using a Deep Learning Model in ArcGIS Pro with Aerial Imagery", detected low head dams, which are dams of consistent shape that are located across a river and allow water to flow over them, were successfully identified using deep learning (Arnold 2023). This study had an 89% success rate identifying "highly visible dams" and "variable levels of accuracy" for dams with vegetation in the way (Arnold 2023). Both of these studies illustrate the ability of deep learning to recognize patterns and shapes, with the latter study introducing something that could pose a complicating issue in this research, namely, vegetation.

There has not been much prior research on the detection and mapping of mobile homes using satellite or aerial imagery. One study entitled, "Multilevel Semantic Labeling of Mobile Homes from Overhead Imagery" by Lunga, et al. (2018), briefly addresses the use of deep learning to identify mobile home parks using convolutional neural networks. In this article, the author used NAIP imagery and 12,000 training samples in order to identify whether a mobile home park could be recognized using this method of deep learning. The study areas for this article range from Nebraska to Utah to Florida, allowing for the recognition of various types of vegetation and layouts of mobile home parks at a 91% accuracy rate when tested on validation data (Lunga et al. 2018). These are promising results for future similar research. Other than this paper, no other articles on mobile home detection using remotely sensed imagery of high spatial resolution were found.

In addition to using deep learning to classify mobile home parks, one must understand the vulnerability level for those living in mobile home parks. Looking at the social impact of severe weather, such as flooding and tornados, on the residents of mobile homes, many issues can be revealed. For example, there are many factors involved in determining whether or not one can evacuate their mobile home during an extreme weather event. Some of these are whether or not the homeowner has a car and if they can fit their family in the car, whether they received a notification in the language they speak, how close is the nearest shelter, and do the residents of the mobile home park have a general sense of safety and knowledge of severe weather? Mobile homes provide affordable housing for many; however, most mobile home parks are not equipped with shelters in the case of a tornado. This is especially relevant because a "single-wide" mobile home can be completely destroyed by tornadoes with wind gusts corresponding to an EF1 rating, and double-wide mobile homes can be completely destroyed by wind gusts indicative of an EF2 rating" (Ash, et al. 2020).

When it comes to demographics, mobile homes are not a well-represented pool in household research data. However, a study done by Sullivan et. al (2021) reveals the demographics of mobile home parks in the Houston area. It was found that mobile home parks in the Houston area tend to be more diverse, with "more Black and Hispanic or Latinx households" than White households. A report from Consumer Finance states that, in the United States, 2.7 million adults between 60 and 69 years old live in mobile homes, more than any other age group (BCFP Data 2014). The second largest age group is 30-39 years old at 2.2 million adults. Finally, income is important in the study of vulnerability factors because the “median annual income of households residing in manufactured housing is $28,374” (George 2016).

CHAPTER 3

METHODS

Data Sources

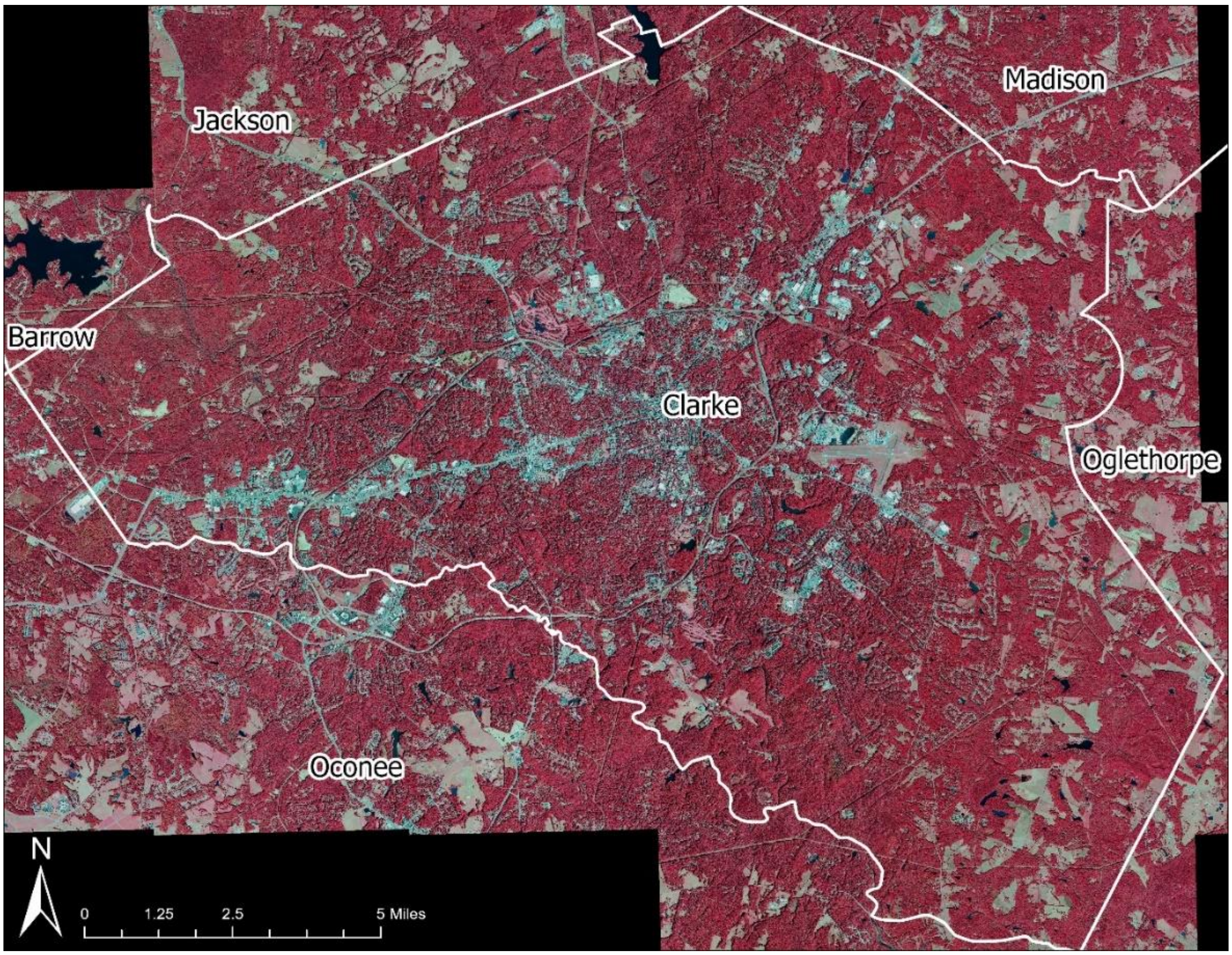


Figure 9 - NAIP imagery of Clarke County with the county boundaries overlaid (USDA 2024).

The main dataset used for this project is high resolution and multispectral aerial imagery from the U.S. Department of Agriculture (USDA) National Agriculture Imagery Program (NAIP). These data were accessed via the NAIP GeoHub, where one can identify an Area of Interest on the ArcGIS Online map interface, and download a .sid file that can be opened in

ArcGIS Pro (USDA 2024). Due to the detailed imagery required for the detection of relatively small mobile homes using deep learning detection analysis (i.e., 1-m pixel resolution) and data size constraints of the NAIP imagery, only Clarke county was used for this aspect of the project, as seen in Figure 9. The most currently available orthomosaic of NAIP imagery is from 2019, encompassing Clarke County. This orthomosaic is 2.2 GB in size and was downloaded to a local drive and uploaded to ArcGIS Pro.

Additional data required for this research include U.S. Census Tract and Census Block boundaries and demographic data for Clarke County and its surrounding counties in order to conduct a vulnerability analysis of the communities in the mobile home parks. Available through the U.S. Census Bureau from the American Community Survey (ACS) in 2018-2022 and Integrated Public Use Microdata Series (IPUMS) National Historic GIS (NHGIS) database, these data include demographic and socio-economic information such as Population Estimates and Population Characteristics, Owner-occupied Housing Rates, Median Gross Rent, Race and Hispanic Origin, Age and Sex, Families & Living Arrangements (with Language other than English spoken at home), Education, Health (with a disability and persons without health insurance), Economy, and Income & Poverty (IPUMS NHGIS 2020, U.S. Census Bureau 2024).

An additional dataset that was accessed in this research is a point file of the locations of existing mobile home parks available for the entire U.S. found on the ArcGIS website. This dataset was created by the Oak Ridge National Laboratory for the Homeland Infrastructure Foundation Level Data (HIFLD) database and was published in September of 2018. With 2281 records, it is an incredibly comprehensive source for mobile home park locations. However, there are mobile home parks that have not been added to this dataset. Additionally, this dataset only marks the parks themselves and not individual mobile homes, meaning that the mobile homes not within a park can go under the radar of rescue teams and emergency services in a time of need.

One of the most important resources in this project is the IPUMS NHGIS database which gives one access to an immense amount of Census data from decades to centuries ago (IPUMS NHGIS 2020). In this case, data from the 2020 Census was used, as this included topics such as race, age, and income. This website allows one to choose a geographic level for datasets. Some of the levels include state, county, block group, and block. For the geographic level, block groups were chosen as the best representation of each of the attributes. "Block groups (BG) are the next level above census blocks," as they contain multiple blocks, aggregating data from the blocks to create a larger area (U.S. Census Bureau 1994). While blocks provide more specific details, it was decided that the difference between groups and blocks was negligible when it came to results, so block groups were used, as visualized by Figure 10. Additionally, NHGIS allows for the download of shapefiles of block groups and other geographic levels. These shapefiles contain an attribute table column that allows for the easy join of tables from NHGIS to the shapefiles. This was used for data including, but not limited to, Black, Hispanic and White populations, and annual household income. Tornado tracks between 1950 and 2022 were also downloaded from the National Oceanic and Atmospheric Administration (NOAA 2023). This feature contains information about the tornados including date, length, and magnitude.

Methods for Data Analysis

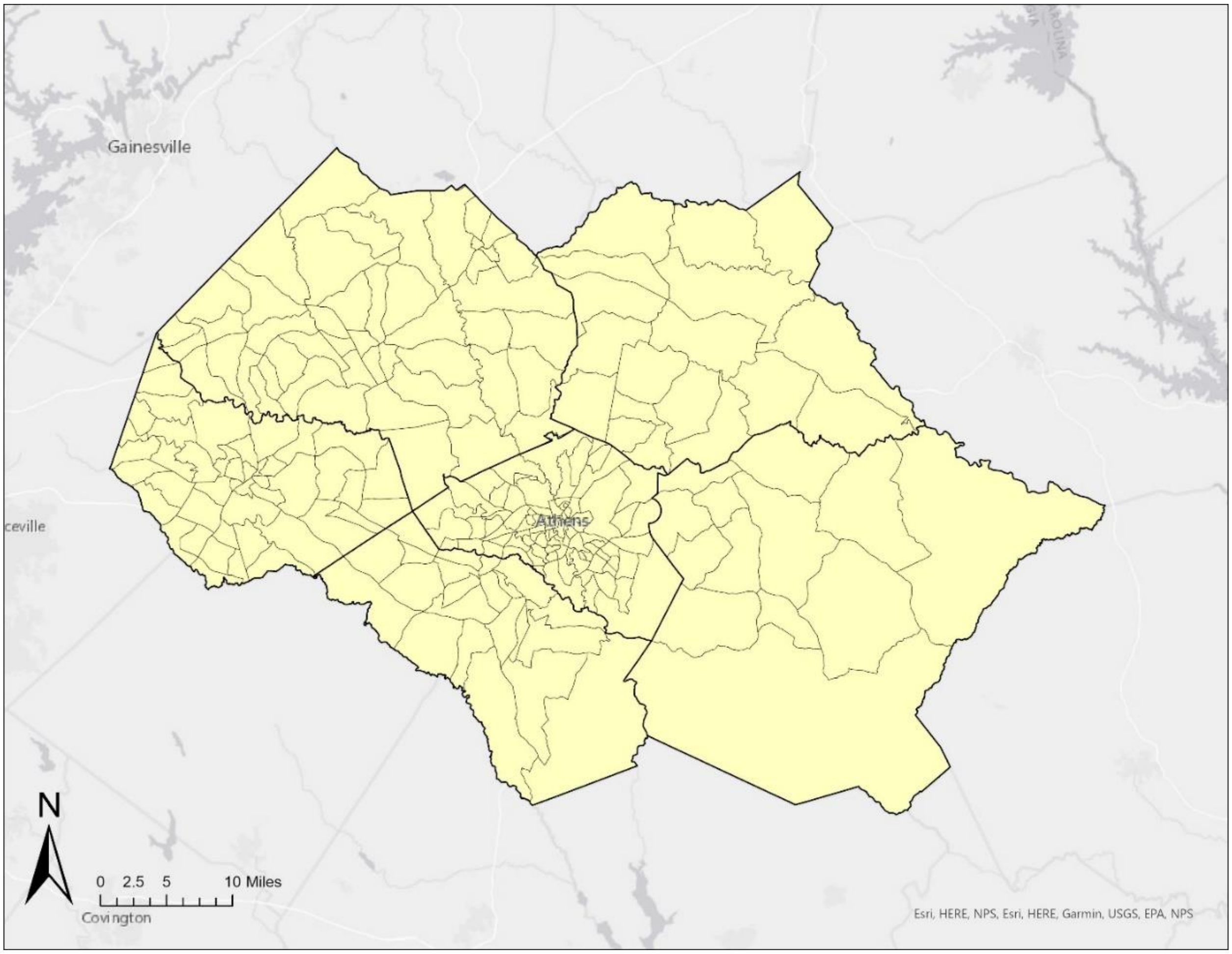


Figure 10 - Map of census block groups within study area (IPUMS NHGIS 2020).

The primary program being used for data analysis in this project is Esri ArcGIS Pro Version 3.2.0. Deep learning analysis was conducted in ArcGIS Pro to determine whether one can identify mobile home parks using NAIP imagery of Clarke County. ArcGIS Pro also was used to conduct a social vulnerability analysis on the areas within and around mobile home parks located in six counties of Georgia to determine if there is a correlation between marginalized communities and likelihood to live in a mobile home park.

The results of mobile home park detection and demographic/socio-economic assessment was used to determine the impact tornadoes and severe weather are predicted to have on marginalized communities living in mobile home parks, especially within a city and surrounding rural area with a history of segregated housing and wealth gaps. A Multi Criteria Decision Analysis (MCDA) was then used to predict the likelihood of vulnerable populations at risk for extreme weather impacts. A MCDA "is used to logically evaluate and compare multiple criteria that are often conflicting to make the best possible decision," with the criteria for this project being locations of mobile home parks, social vulnerability by Census tracts and/or blocks, and risk of tornadoes based on past data (Ryan and Nimick 2019).

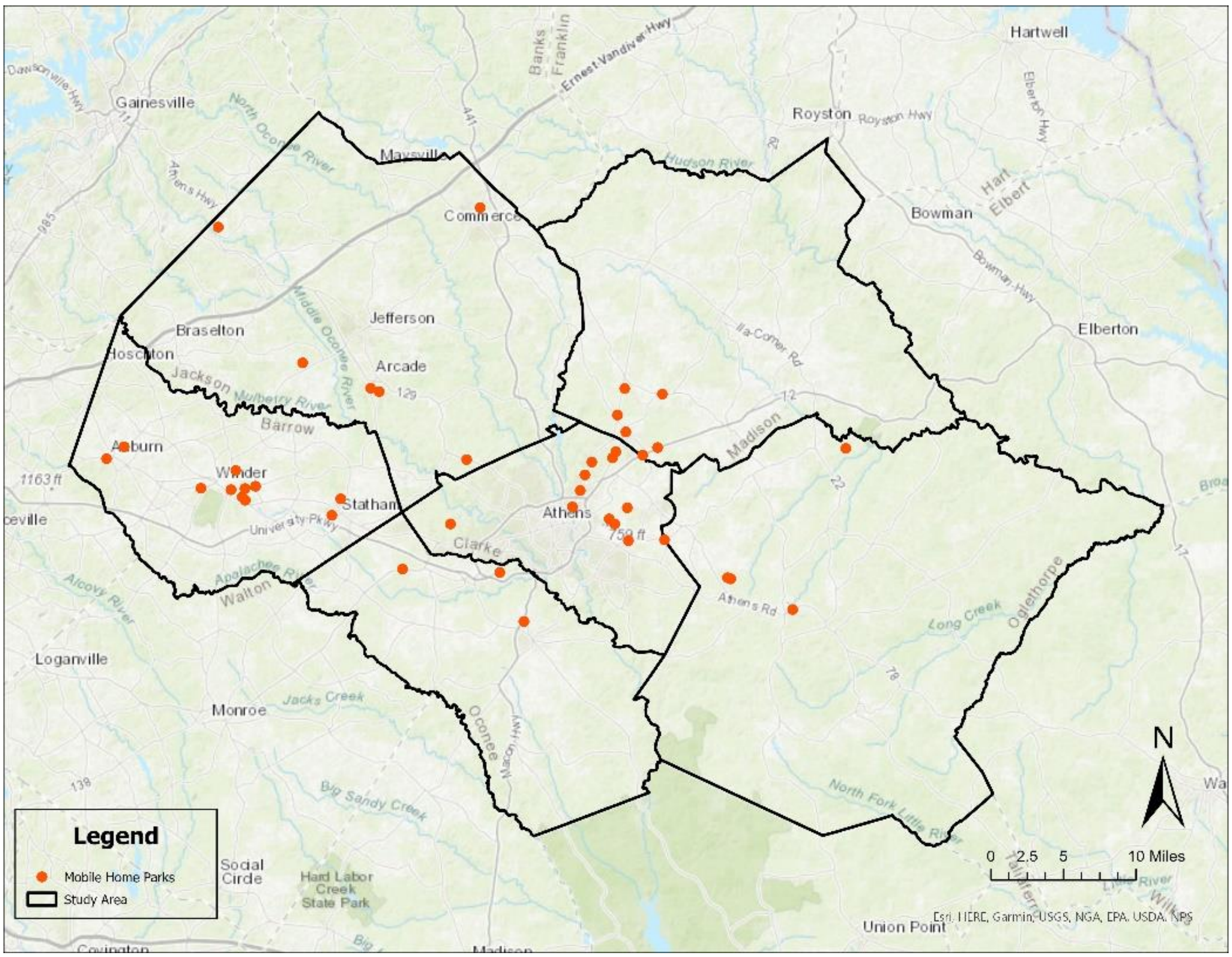


Figure 11- A map of the mobile home parks located within the study area with each dot representing one mobile home park (ESRI 2019).

Initial data manipulation involved clipping nationwide data such as the point locations of existing mobile home parks to the county boundaries which left 42 mobile home parks within the selected range (Figure 11). These 42 parks are distributed around Clarke and surrounding counties mostly along highways and close to the city of Athens with only a few mobile home parks being in Oglethorpe and Oconee county, likely due to the generally lower populations in these counties. The largest cluster of mobile home parks is located in Northeast Athens. These 42 mobile home parks provide adequate resources to create image samples in order to establish enough data for the deep learning model to train and validate predicted mobile home parks from the 2021 NAIP imagery.

Deep Learning

Deep learning, according to ESRI (2024), "uses computer-generated neural networks, which are inspired by and loosely resemble the human brain, to solve problems and make predictions." This is more specific and in depth than pixel-based classification as it learns from itself and can recognize patterns, unlike other traditional methods of classification such as maximum likelihood that statistically classifies individual pixels based only on their spectral reflectance (Lillesand et al. 2015). The reason deep learning was chosen instead of traditional classification was while some positive initial results were found using segmentation and classification of Planet imagery of 3.7-m resolution in ArcGIS Pro, much of the landscape classification was confused as developed areas that were not mobile home parks. Deep learning is able to recognize the pattern of a mobile home park (i.e., mobile homes are generally similar in size, shape and arrangement within designated parks) and classify mobile home parks more specifically as opposed to the rough estimates provided by traditional pixel-based classification.

In order to accommodate ArcGIS Pro's raster size limits with regards to deep learning analysis, NAIP imagery covering all six counties in the study area was deemed too large to be analyzed. Therefore, only NAIP imagery for Clarke County, the central county in the Study Area, was downloaded from the USDA NAIP GeoHub. Training set samples or image chips were created in the “Label Objects for Deep Learning” tool from the NAIP orthomosaic of Clarke County and a small amount of its surrounding area.

In order to conduct deep learning in ArcGIS Pro 3.2, the Deep Learning Library must be installed from GitHub, where the version of ArcGIS Pro must match the installer version. Upon completion of this installation, a Deep Learning tool will appear on the banner for imagery within ArcGIS Pro. This tool includes functions such as “Label Objects for Deep Learning” and “Train Deep Learning Model,” both of which are used in the deep learning process conducted in this research. “Label Objects for Deep Learning” allows the user to create training samples for a deep learning model. In order to do this, polygons are drawn around target objects (Figure 12). They are then exported as training data. The amount of training samples created is entirely up to the user. Samples were taken of both individual mobile homes and sections of mobile home

Figure 12- Examples of polygons drawn around mobile homes for training samples.

parks in order to get a range of samples. Areas that were chosen were mostly clear of vegetation and other obstructions such as clouds in order to get the best results.

The "Train Deep Learning Model" tool takes the output from "Label Objects for Deep Learning" and uses it to train the deep learning model, in this case a MMDetection model, which is a type of object detection model. Parameters can be set either automatically or by the user. From here, the training data previously created is pulled from its folder. A time limit can be set in addition to other customizations including various parameters for neural networks and environments. The length of time the model takes to run depends on the storage capacity of the computer's GPU, or graphics processing unit. The training time for this model took approximately four hours, based on 100 training samples and a computer with a NVIDIA GeForce GTX 1660 Ti graphics card. Computers with more powerful graphics cards can process the training data at a faster rate. Once the "Train Deep Learning Model" runs, a deep learning package (.dlpk file type) will be created in the output folder.

Once the model has been created, the next step is to use the "Detect Objects Using Deep Learning" model. This model is where the target object will be detected by the neural network and labeled as such. Within the tool, a raster must be input in addition to the model definition created by the "Train Deep Learning Model" tool. The environments section of this tool allows one to choose things such as an output coordinate system, cell size, and processor type. Selecting processor type is important because this determines the processing unit that is used by ArcPro to conduct the detection. For this reason, the processor type chosen was the GPU with the NVIDIA graphics card. The time it takes to run this model also depends on the specifications of the graphics card. For the mobile home model, it took approximately 12 hours, or overnight to complete the deep learning model.

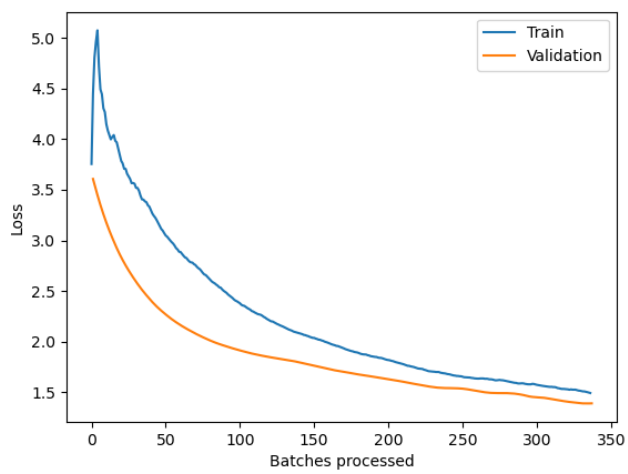


Figure 13- Loss graph showing Loss compared to Batches processed.

Figure 14 - Ground truths/predictions created by the model.

In addition to the deep learning package, the output folder will contain a folder entitled "ModelCharacteristics." This folder includes a loss graph (Figure 13) and a series of ground truths/predictions (Figure 14). The loss graph "gives … insights into how the model's performance improves over time by measuring the error (or dissimilarity) between its predicted output and the true output" (Ibrahim 2024).

In the case of the model created by the mobile home training samples, loss is much higher at the beginning of the batch process and gets significantly smaller as the number of batches increases. The term “batches” refers to how many image chips are processed in a given amount of time. Due to computer constraints, image chips were processed in small batches, leading to a larger number of batches processed. The “decrease in the loss value suggests that the model is making better predictions, as the loss represents the error or dissimilarity between the predicted output and the true output” (Ibrahim 2024). Therefore, as the computer got toward 350 batches, the true output got more accurate.

In addition to the loss graph, a series of ground truths/predictions are given. These allow the user to see a preview of what the model believes the detected objects are (i.e., predictions) compared to the training sample input to the model (i.e. ground truths). Due to the fact that the preliminary model was successful, it was possible to go ahead with the full deep learning analysis.

Multi Criteria Decision Analysis

The Multi Criteria Decision Analysis (MCDA) aspect of this research focuses on developing a model that ranks tornado disaster risk and social vulnerability for residents of mobile home parks within six northeastern Georgia counties. The model incorporates four major variables: mobile home park locations, prior tornado tracks since 1950, race, and income level. In order to get an accurate depiction of what a tornado’s impact would be on a mobile home park, the model takes into account wind damage in areas along known tornado tracks. Tornados are not predictable, therefore, records of past tornado tracks over the study area dating back to 1950 were used as examples of tornado risk and damage paths for this research.

The mobile home parks/homes used in the MCDA model were taken from both the Oak Ridge National Laboratory shapefile of all mobile homes in the six-county study area and the new mobile homes/mobile home parks established by the deep learning method. In order to do this, the footprints of predicted mobile home parks determined by the deep learning analysis were cleaned so each mobile home or mobile home park was represented by one new point. Then, these additional 12 points in Clarke County were merged with the already existing mobile home park point locations, leading to a total of 54 mobile homes and mobile home parks within the study area of all six counties.

The buffer tool in ArcPro is a geoprocessing tool that allows the user to input a feature and determine the distance of the buffer, to create a buffer polygon of a certain distance around the feature. Additionally, it allows the user to select buffer options such as side type, end type, method, and dissolve. In the case of this project, all of these factors were left to their default settings as changing them is not necessary for the needs of this research. Tornados come in a wide range of sizes based on various factors but the width of the tornado track damage usually ranges from 300 yards (274.3 meters) to 500 yards (457.2 meters), and the width of a typical tornado wind damage path is between 1 mile (1.6km) and 2 miles (3.2km) (FEMA 1996, NWS 2024). Due to the fact that the impact of tornados can be felt beyond just the base of the tornado, wind damage wider than the estimated tornado track width was also considered by buffering. Four buffers, two for possible tornado tracks and two for wind damage were created around the tornado track lines, (i.e., two for tornado path width and two for damage path width), at the respective sizes mentioned above. Due to how the buffer tool works, the buffer distance must be half of the desired width of estimated tornado damage along the track. Therefore, the buffer distances converted to meters were 150 yards (137.2 meters), 250 yards (228.6 meters), .5 miles

(804.7 meters), and 1 mile (1,609.3 meters). These longer buffer distances were selected based on average wind damage distances.

In order to get the various demographic statistics about the study area, data were downloaded from the NHGIS website. These data were then joined to the block groups shapefile, using the GISJOIN field, in order to have the data collected in one place. Providing the demographic data for the MCDA, these data were then combined in order to conduct an analysis of which demographics are more prone to the impact of tornados on mobile home parks.

CHAPTER 4

RESULTS

The output of "Detect Objects Using Deep Learning" is a series of polygons drawn around areas that are predicted to be mobile homes or mobile home parks. The output for the whole model is shown in Figure 15. It is somewhat difficult to visualize the predicted mobile home parks from a zoomed-out county level since the footprints of identified mobile homes are so small. The outputs of detected mobile homes and parks are mostly evenly spread out over Clarke County and its surrounding areas.

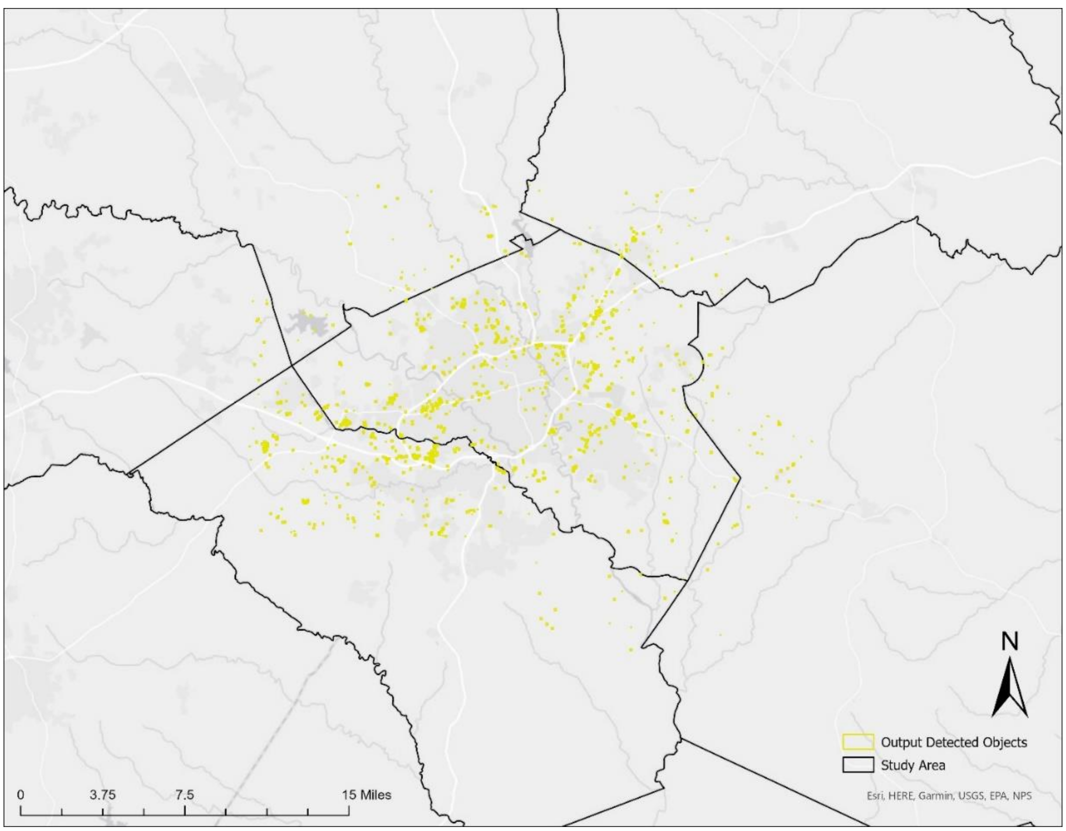


Figure 15-Objects detected by model. Each yellow polygon represents what the model identifies as a mobile home/mobile home park.

After creating the output, it was necessary to determine which areas it accurately detected as mobile homes. To maintain Clarke County as the main focus for the deep learning aspect of this project, the shapefile of outputs was clipped to just Clarke County. In order to determine accuracy, the outputs were manually examined using visual interpretation of the high-resolution image base map in ArcGIS Pro to determine which predicted footprints actually fall over mobile homes/mobile home parks. It was determined that, out of the 669 detected objects, there were 42 accurately detected parks/homes. An accurate detection is determined by whether it contained a part of or a whole mobile home or mobile home park. This means the model was 6.3% accurate. While this is not a high percentage, the results are still promising.

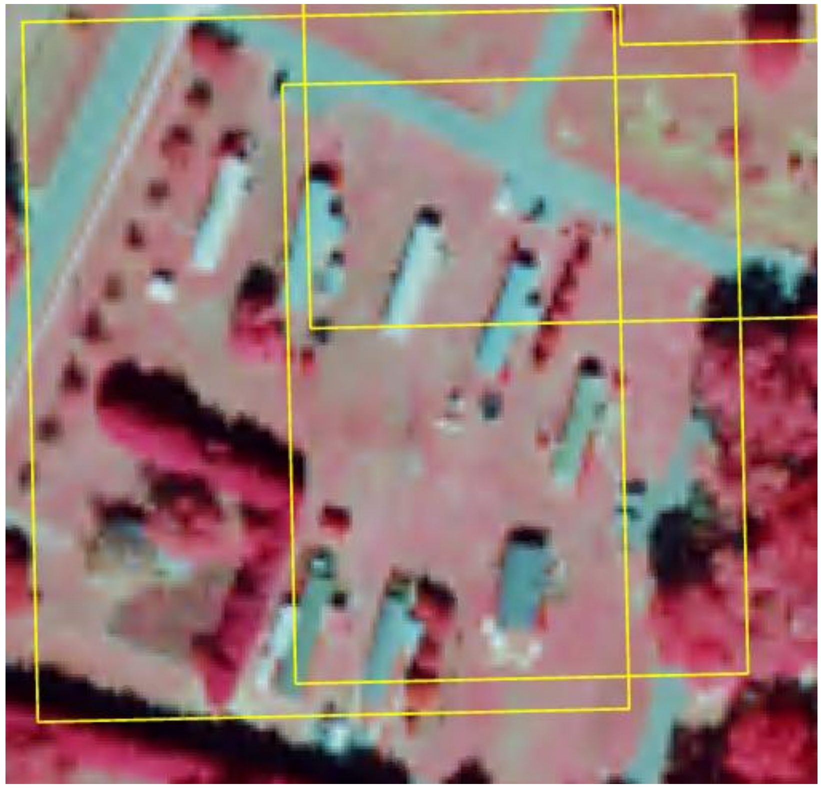


Figure 16- Example output of detected mobile home parks.

Figure 16 is a zoomed in view of example output. As illustrated, the model did not necessarily detect individual mobile homes in this case, but the park itself. However, it did also detect individual mobile homes not listed in the original mobile home shapefile, due to the fact that they are singular mobile homes and not parks as shown in Figure 17. Both the detection

Figure 17- Individual detected mobile home.

of individual mobile homes and mobile home parks are deemed to be successful results, and are counted as part of the 6% accuracy. The model is likely recognizing the pattern of mobile home parks and individual mobile homes, with the individual mobile homes lined up in rows with a similar amount of space between them and similar shaped buildings condensed into one area. The mobile home park represented in Figure 16 is one that had not been represented in the original mobile home shapefile either, meaning the model accurately detected a new mobile home park. In addition to detecting already existing and new mobile home parks, the deep learning model also detected recreational vehicle (RV) parks as seen in Figure 18.

Figure 18- Example of detected recreational vehicle (RV) park.

Additional detections that are of note are ones that were not mobile homes/mobile home parks but instead objects that are the general shape of a mobile home, including cars parked next to one another and air conditioning units on top of buildings. Figures 19 and 20 are examples of false positive detections showing a similarity between these objects shape and pattern and mobile home parks.

Figure 19 and 20- Objects detected by the deep learning model.

Figure 21 represents the combined preexisting mobile homes/mobile home parks from the Oak Ridge National Laboratory (ORNL) dataset combined with the mobile homes/mobile home parks detected by the deep learning model. This is why there are a larger amount of mobile homes/mobile home parks in Clarke county. 12 mobile homes/mobile home parks were added to the existing points in the Oak Ridge dataset. Figure 22 represents the 46 tornados that have passed through the study area since 1950, with increasing red colors representing the various widths of both the damage paths and the actual tornados. The individual dots with concentric circles around them are where a tornado simply touched down for a split second and did not remain on the ground.

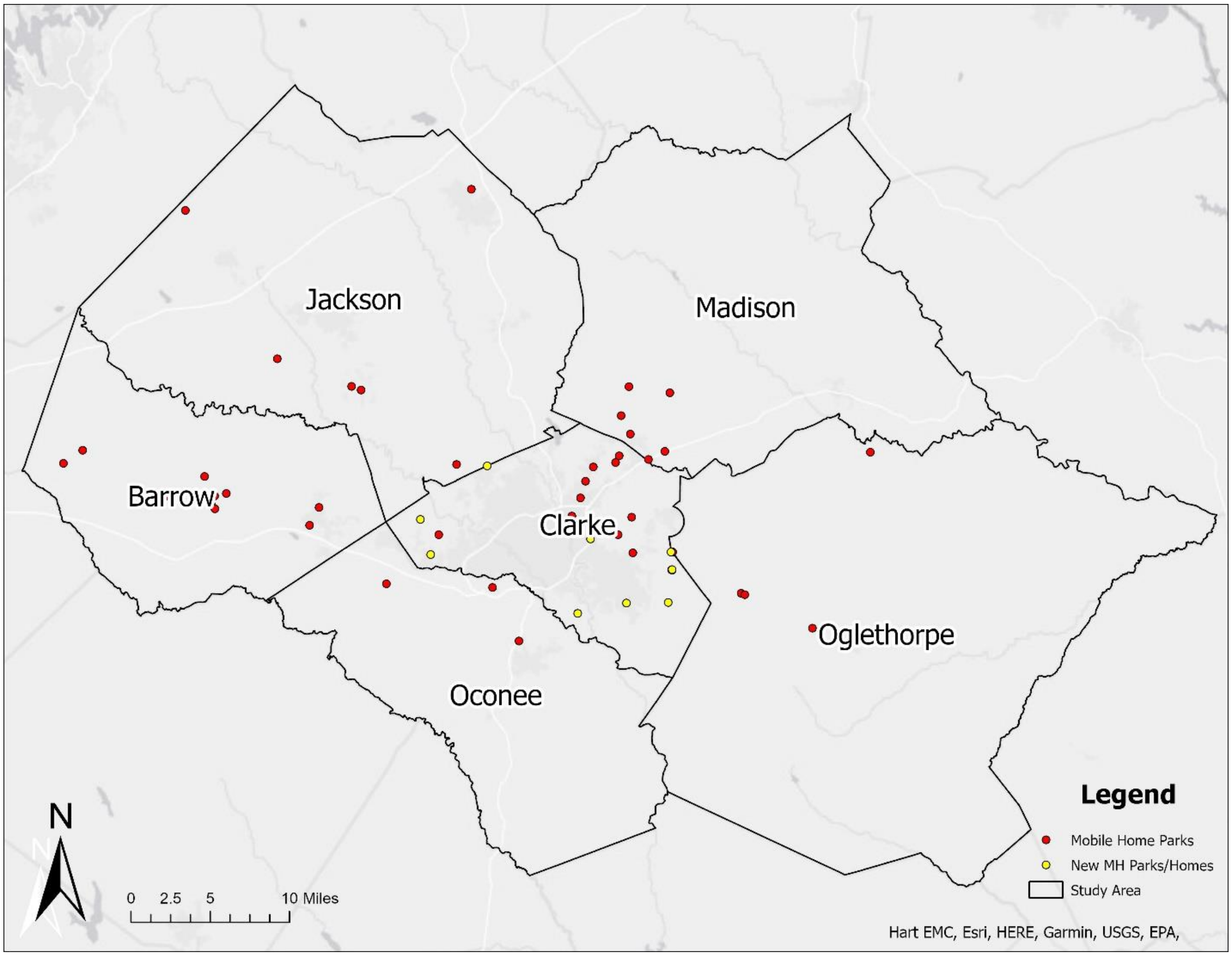


Figure 21- A map of the preexisting mobile homes/parks in the ORNL data set (red) and new mobile homes/parks detected with deep learning (yellow) within the study area.

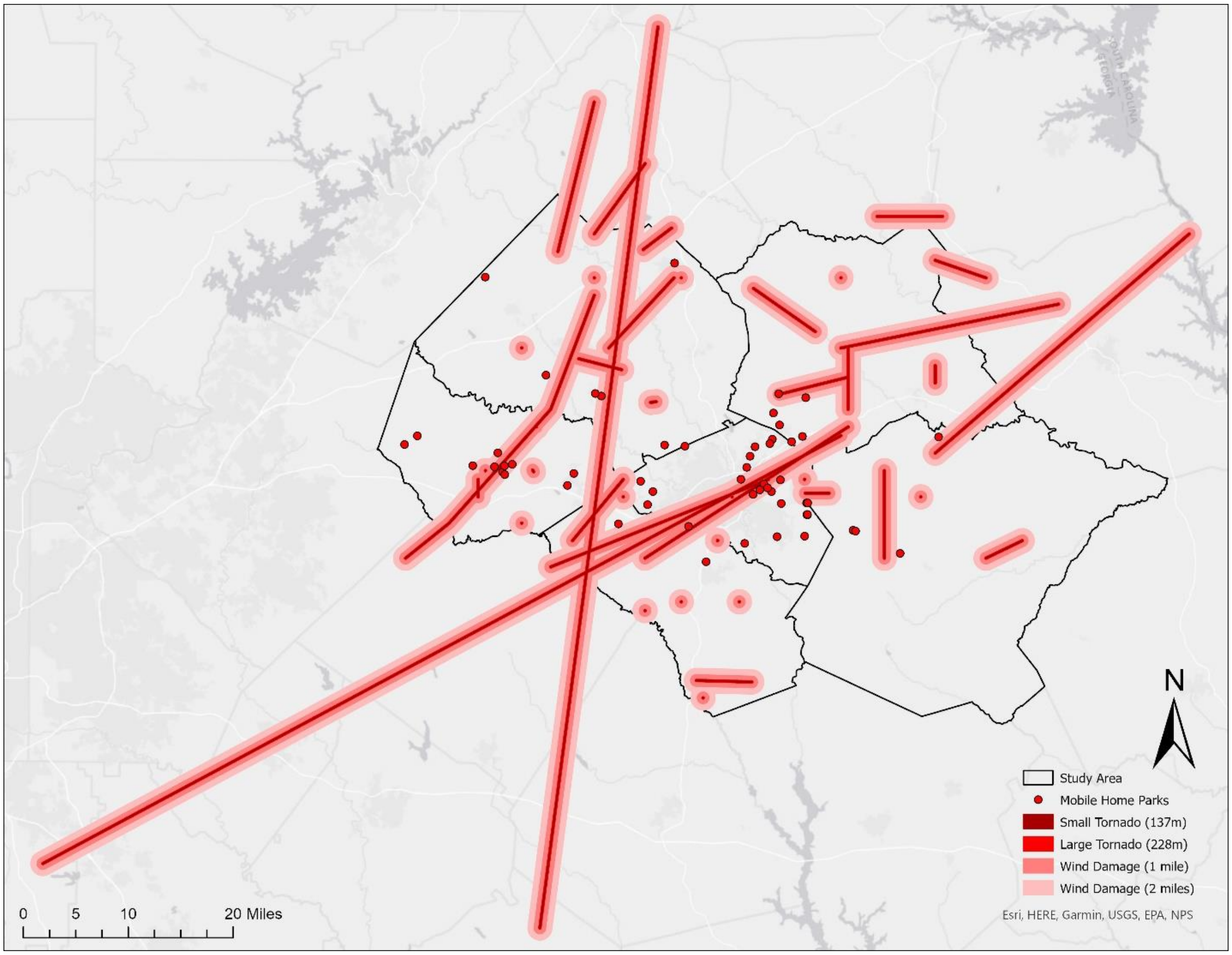


Figure 22 - The various tornado tracks/wind damage paths compared to locations of mobile home parks.

The selection tool in ArcGIS Pro was utilized to determine how many mobile home parks were located within each of the risk areas. Table 3 compares the width of the tornado or wind damage path to the number of mobile home parks within its track. The total number of mobile home parks per tornado track buffer is cumulative. For example, within the wind damage 2-mile category, those 20 mobile home parks/mobile homes also include the parks/homes within the small tornado range. A total of 20 out of 54 mobile home parks/mobile homes located within the study area were determined to have been in the path of either a tornado or the wind damage from a tornado, meaning 37% of the mobile homes within the study area would have been impacted by past tornados. A total of 7 newly detected mobile home parks/mobile homes also were located within the 1- and 2-mile wind damage zones. The selected mobile home parks/mobile homes were then exported as a new feature and maps were created that represent the various factors compared to the tornado tracks covering the entire study area.

Table 3- Width of tornado/wind damage paths and how many mobile homes/mobile home parks are in its path within the study area.

Tornado Size and Wind Damage	Buffer Distance (meters)	# of Mobile Homes/Mobile Home Parks in Path	New Mobile Homes/Mobile Home Parks in Path Detected by Deep Learning
Small Tornado (300 yards wide)	274.34m	1	0
Large Tornado (500 yards wide)	457.2m	1	0
Wind Damage (1 mi)	1609.3m	8	3
Wind Damage (2 mi)	3218.7m	20	4

Figures 23, 24, and 25 depict the MCDA and spatial overlay of: 1) mobile home parks/mobile home locations; 2) prior tornado tracks with small (300 yds. wide) and large (500 yds. wide), along with wind damage buffers out to 1 and 2 miles (1609.3m and 3218.7m, respectively; and 3) population size by U.S. Census block groups by race (Black, White and Hispanic/Latinx). Figure 26 depicts a similar spatial overlay of mobile home parks/mobile homes, prior tornado tracks with damage buffers and median income by U.S. Census blocks.

Figure 23 represents a spatial overlay of the tornado/wind tracks, mobile homes, and the Black population by block group. The tornado tracks overlap with the block group that has the highest population of Black residents within the entire study area, at 1,232 people as of 2020. This block group is located in Northeast Clarke county and is home to four mobile homes/mobile home parks.

Figure 24 represents the tornado tracks/wind damage compared to the White population within the study area. There is a generally higher population of White citizens throughout the study area, however it can be seen that the area in Northeast Clarke County, an area with more mobile homes, the White population is lower. This can also be seen in central Barrow County, where the white population is lower, but the amount of mobile homes is higher. While there are tornados that strike areas with high White population density, mobile home parks tend to be in areas with a lower White population.

Figure 25 represents the comparison of Hispanic or Latinx population with the tornado tracks and locations of mobile home parks. The cluster of mobile home parks in Northeast Clarke County are also where the largest Hispanic/Latinx population resides, and is the most impacted by previous tornados.

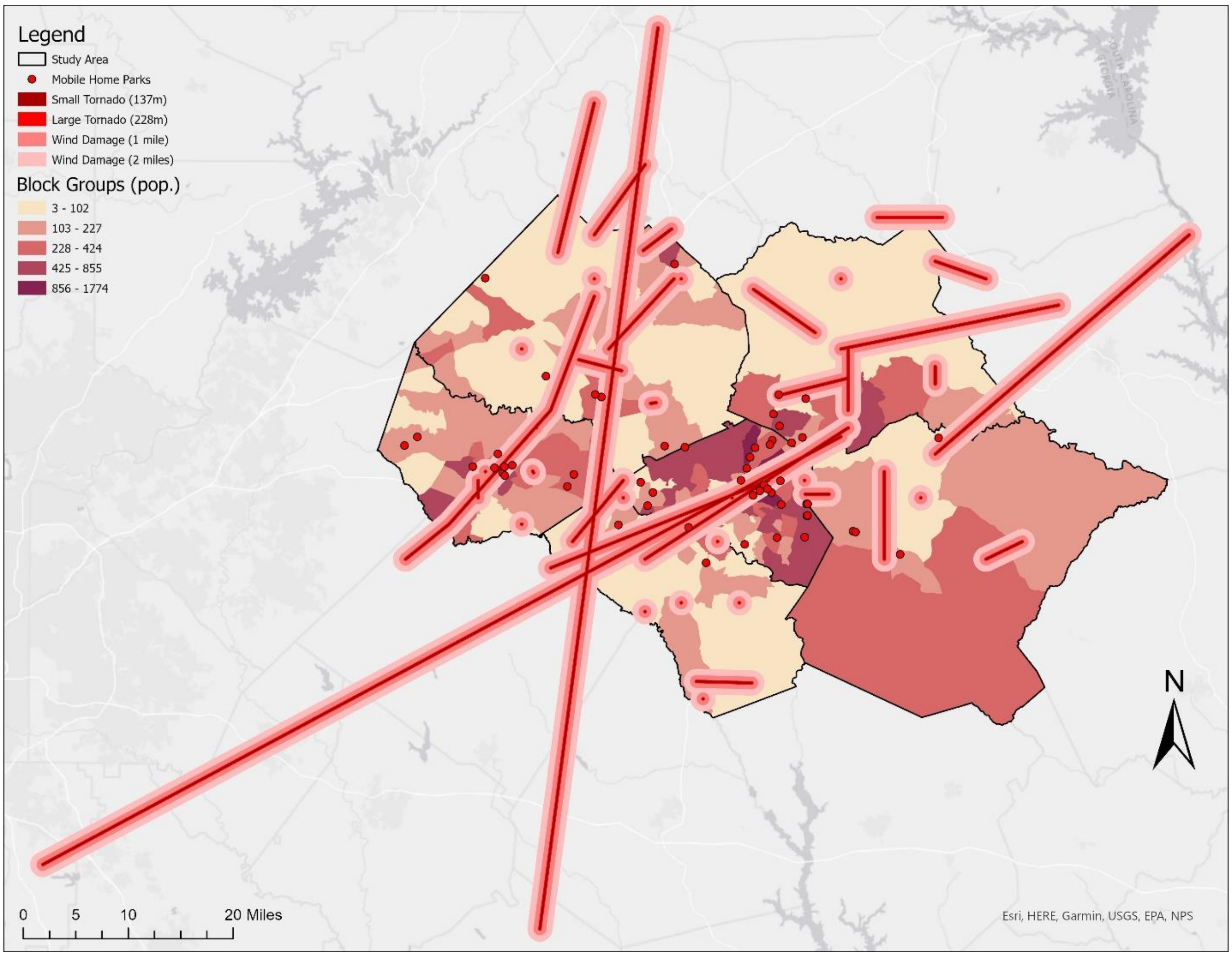


Figure 23- A spatial overlay of mobile home parks/mobile homes, prior tornado tracks buffered to represent small and large tornado tracks of 300 and 500 yard widths, respectively, wind damage along tornado tracks out to 1 and 2 mile widths and Black population by U.S. Census block groups.

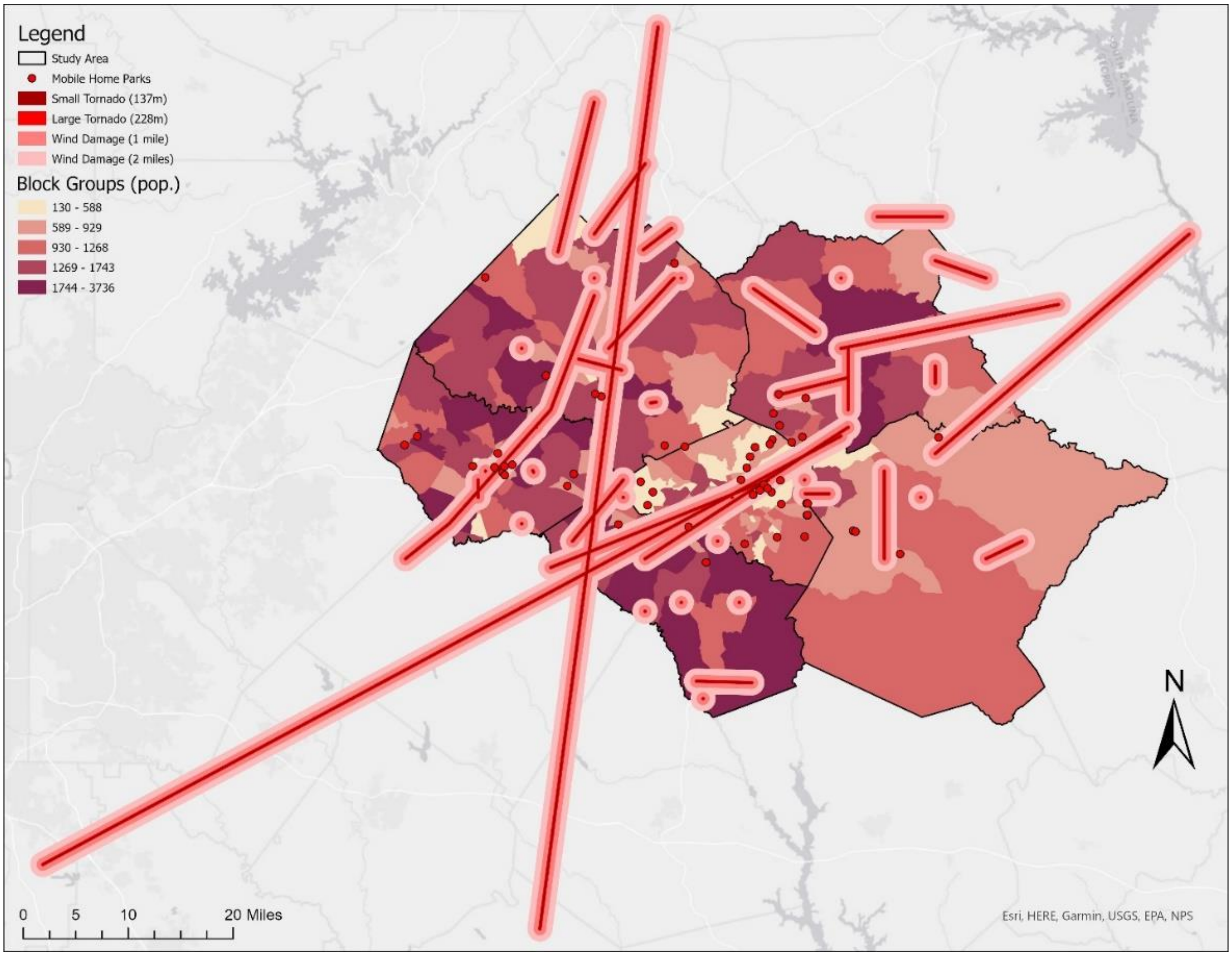


Figure 24- A spatial overlay of mobile home parks/mobile homes, prior tornado tracks buffered to represent small and large tornado tracks of 300 and 500 yard widths, respectively, wind damage along tornado tracks out to 1 and 2 mile widths, and White population by U.S. Census block groups.

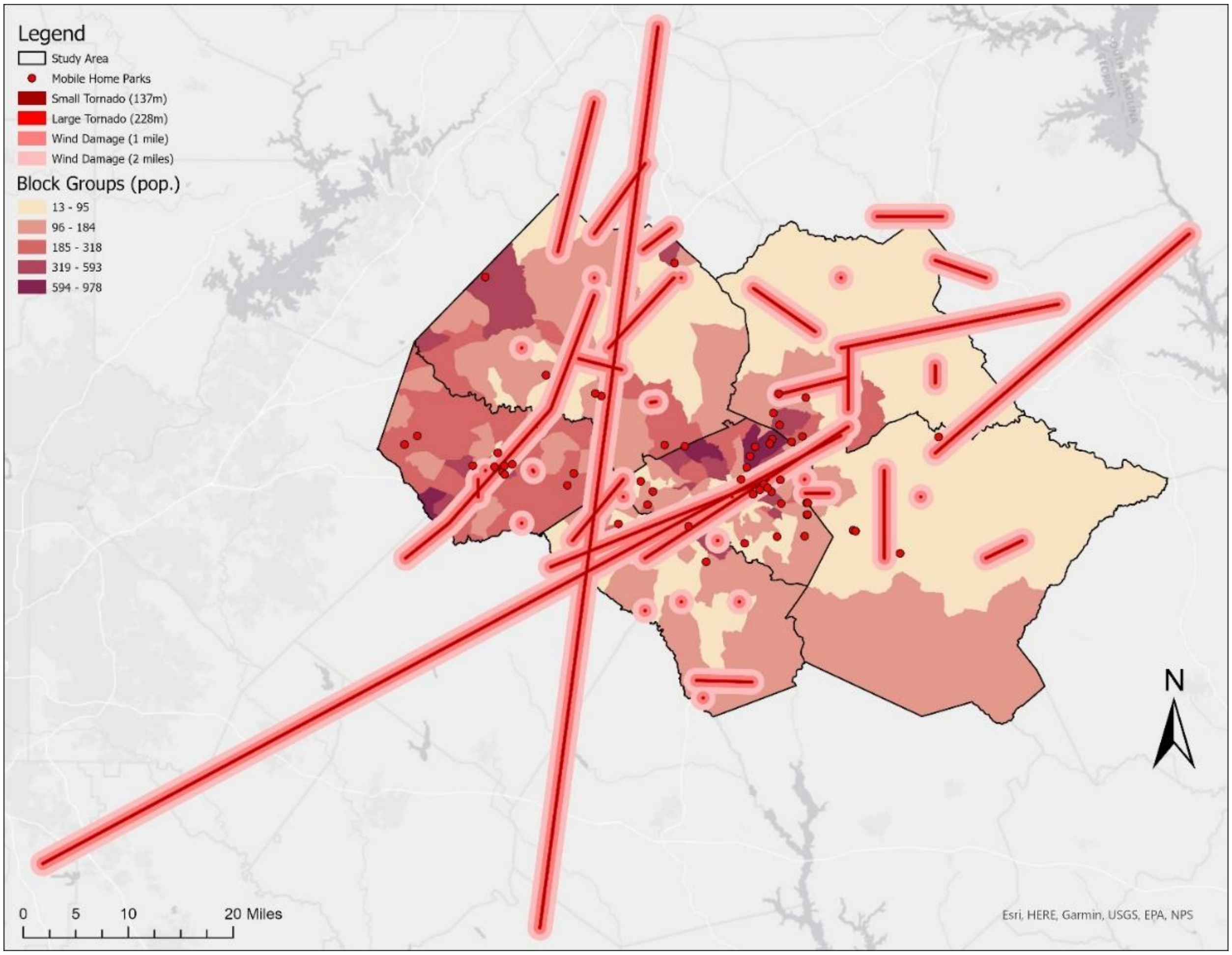


Figure 25- A spatial overlay of mobile home parks/mobile homes, prior tornado tracks buffered to represent small and large tornado tracks of 300 and 500 yard widths, respectively, wind damage along tornado tracks out to 1 and 2 mile widths, and Hispanic or Latinx population by U.S. Census block groups.

Many of the mobile home parks within the study area tend to be in lower income block groups. On only one occasion is a mobile home park found in the block group with the highest income level. Figures 26 and 27 best illustrate this in Northeast Clarke County, where seven of the mobile home parks within the study area are also in the lowest income bracket. Based on the MCDA, the most at-risk area is in Northeastern Clarke county, due to its high count of mobile homes and non-White, Hispanic and/or Latinx, or low-income residents.

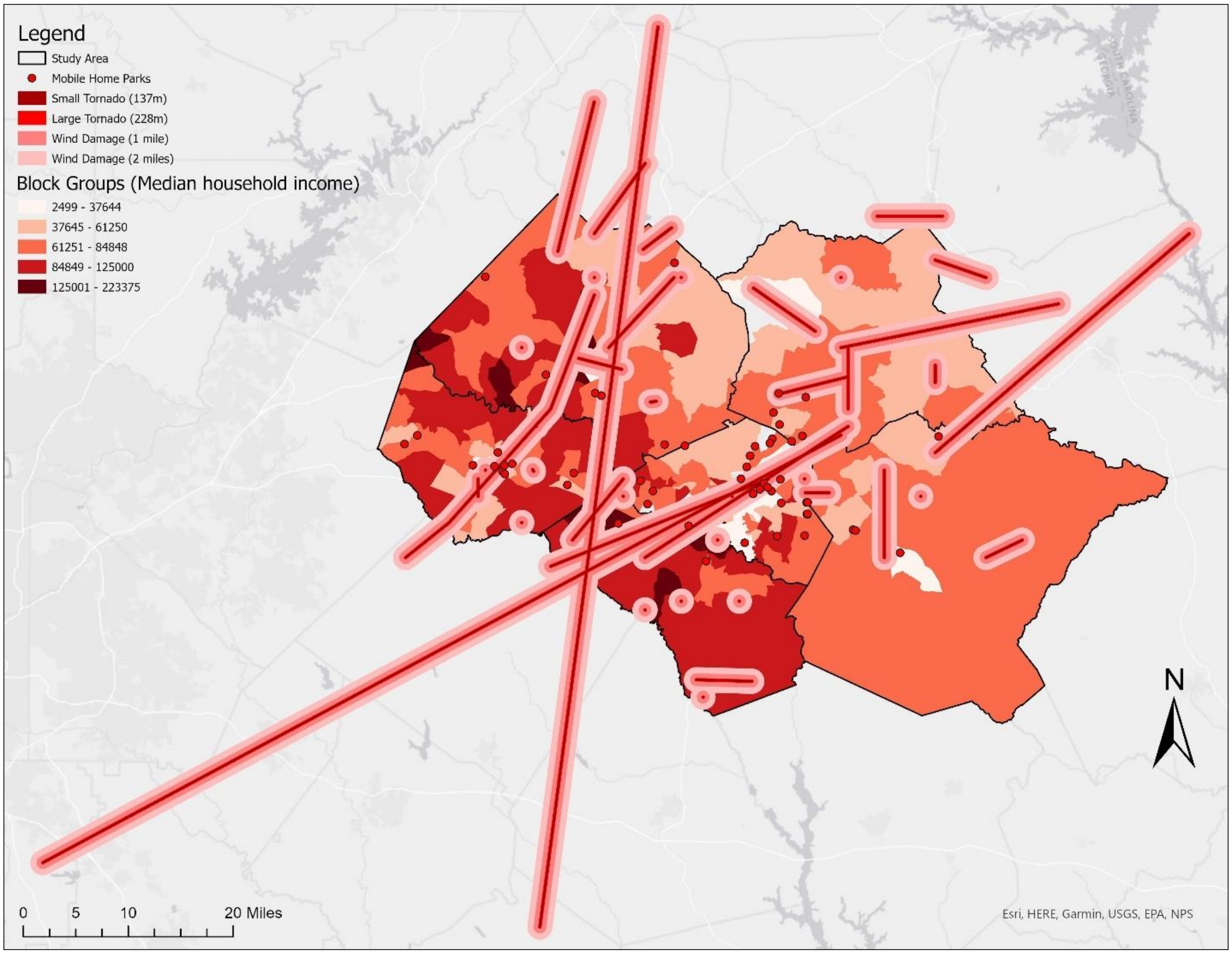


Figure 26- A spatial overlay of mobile home parks/mobile homes, prior tornado tracks buffered to represent small and large tornado tracks of 300 and 500 yard widths, respectively, wind damage along tornado tracks out to 1 and 2 mile widths, and income by U.S. Census block groups.

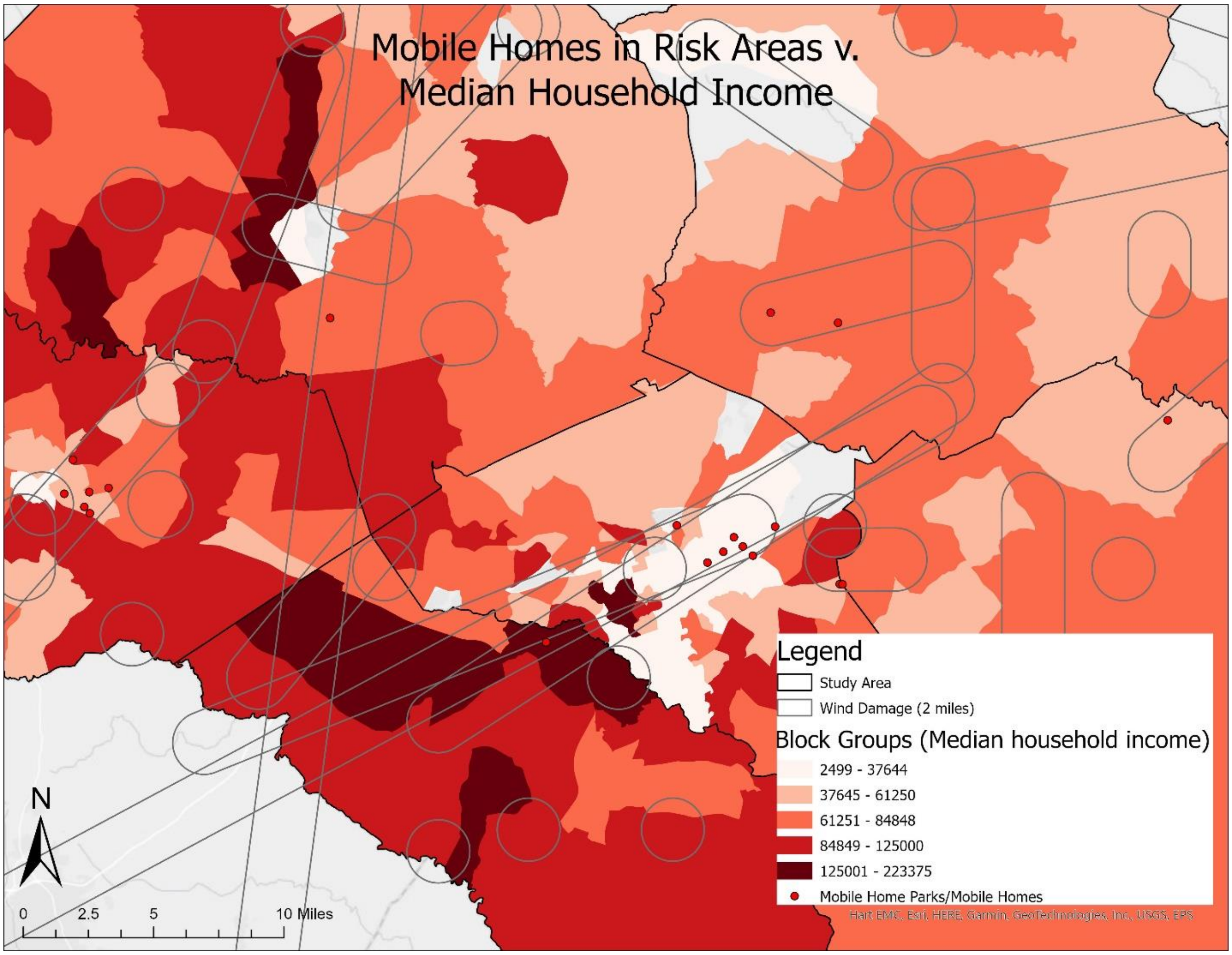


Figure 27- Mobile homes in risk areas vs. median household income.

CHAPTER 5

DISCUSSION

Deep learning is an evolving form of artificial intelligence that can be incredibly useful in geographic spaces. The deep learning model in this project used approximately 100 training samples and was able to identify both individual mobile homes and mobile home parks, in addition to a recreational vehicle (RV) park (see Figure 18). While this model had a number of incorrect outputs, most of which being false positives, it is promising that it did detect mobile home parks and individual mobile homes. Additionally, it detected 12 mobile home parks not represented by the Oak Ridge National Laboratory dataset. This illustrates that the model, despite only having a 6% success rate, can be used to detect new mobile homes and mobile home parks, along with additional forms of vulnerable housing such as RVs and RV parks. Furthermore, many of its incorrect outputs were similar to mobile homes/mobile home parks. These are likely due to their shape and color, with the air conditioning units seen in Figure 19 being rectangular and white on top and the cars in Figure 20, like mobile homes, are next to one another and similar in size and color. These results may be improved by adding more training sets of mobile home parks/mobile homes located in the surrounding counties, incorporating LiDAR data and/or using imagery of a higher spatial resolution.

Figure 28 represents the mobile home parks located within the wind damage 2-mile buffer compared to median household income. While previous tornado tracks cannot be used to determine future ones, comparisons can be made between where mobile homes are located to factors such as household income in order to determine risk based on vulnerability factors. As illustrated by Figure 26 and 27, 7 of the mobile home parks previously impacted by tornados are located within lower income areas, with a cluster of them being in central Clarke county and having the lowest income bracket of median household income per year. Due to mobile homes being an affordable option for those who cannot afford increasing apartment and housing costs, this is an understandable outcome. There are five mobile home parks/mobile homes in higher income brackets, with one being in the highest bracket. Due to the vulnerability of mobile homes to severe weather and tornadoes, and with those who are in lower income brackets to be more likely to live in mobile home parks, it can be inferred that those who reside in mobile homes are more vulnerable to the impacts of tornados. Shivers-Williams and LaDue reveal in their paper that tornado fatalities are 15-20 times greater than those who live in single-family home. With tornado fatalities being more likely for those living in mobile homes/mobile home parks and the demographics of mobile home parks, it can be seen how marginalized communities can be disproportionately impacted by tornados (Shivers-Williams and LaDue 2022).

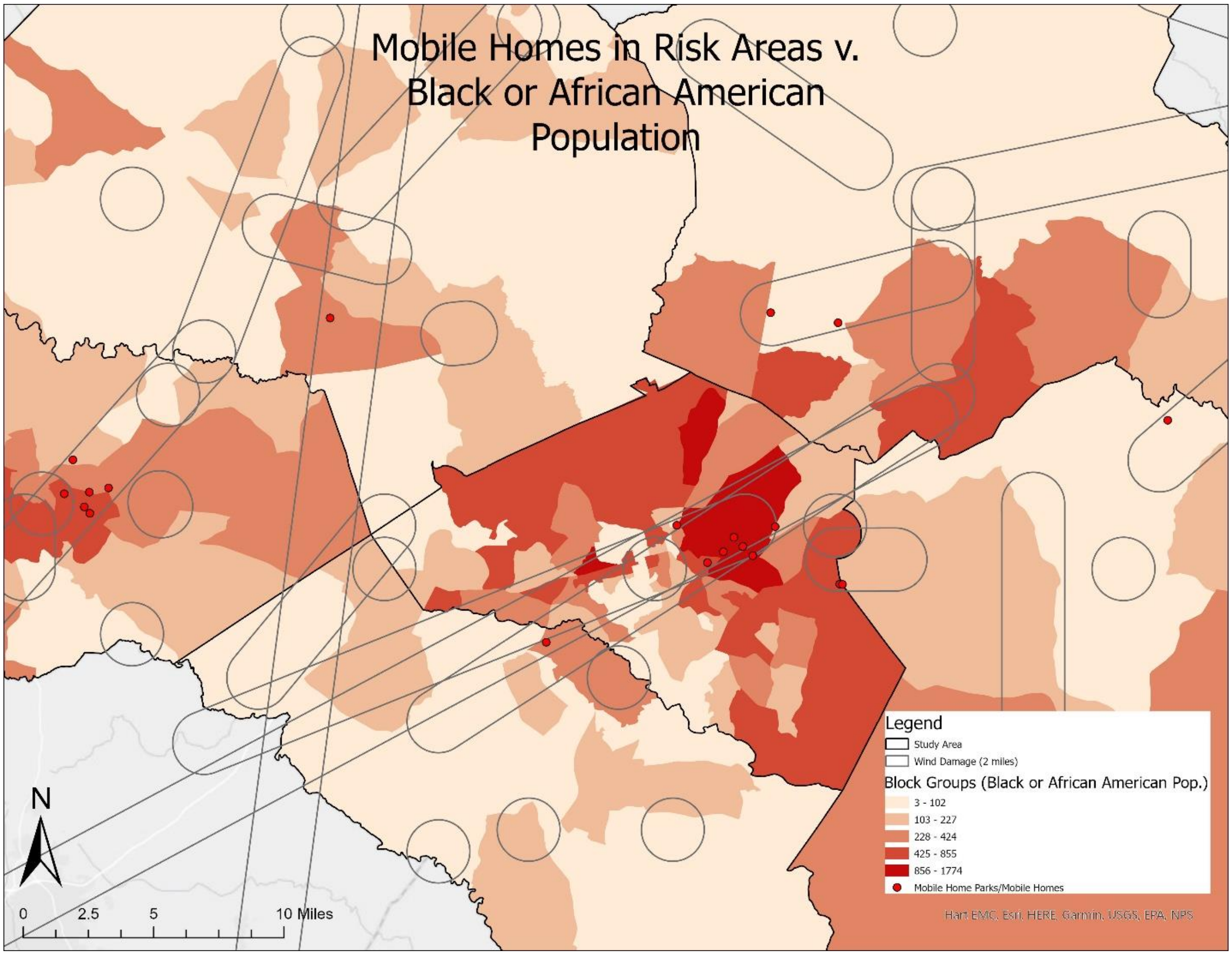


Figure 28- A map of mobile homes in risk areas vs. Black or African American population.

Figure 29 illustrates the White population of the study area versus the mobile home parks located within the previous tornado track wind damage paths. The U.S. Census block groups are symbolized with a darker red color as the White population increases. There are multiple points to note in this map regarding White population size per block group and location of mobile home parks. One is that the central county, Clarke, has the highest White population in the center of the county where the University of Georgia and the historical downtown businesses are located. The surrounding areas have much lower White populations. In addition to this, the cluster of mobile homes in Clarke County are located in a majority non-White area. The other mobile homes located in the surrounding counties of the study area are also in areas with lower White populations. Most notably, the cluster of six mobile homes located East of the University of Georgia block group is in a predominantly non-White area. While this information cannot be used to make a claim that fewer white people live in mobile homes, it can be used to infer that, in the case of this study, the risk the White population faces from living in mobile homes is lower.

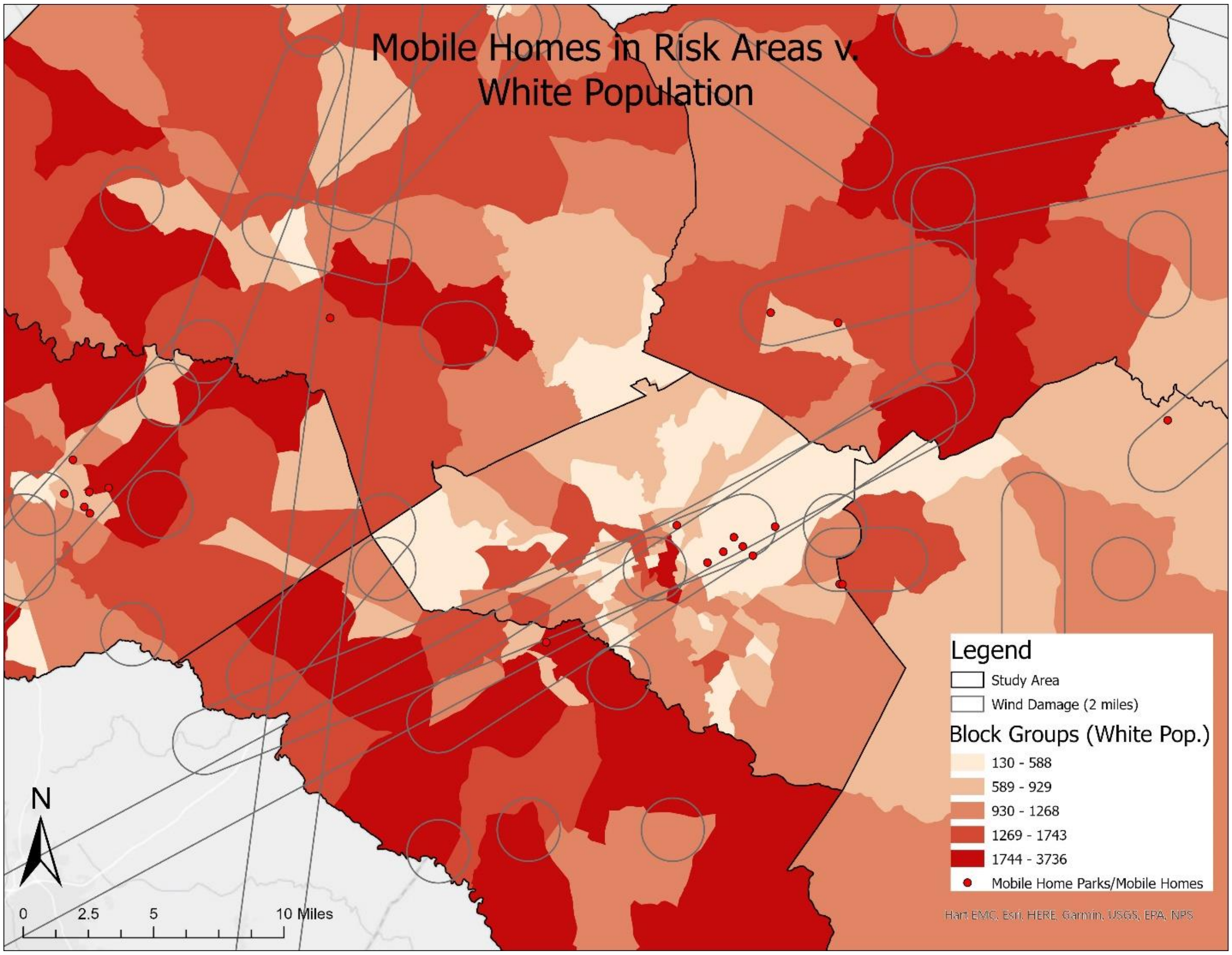


Figure 29- A map of mobile homes in risk areas vs. White population.

As seen in Figure 30, many mobile home parks/mobile homes are located within areas that have a higher Hispanic or Latinx population. The cluster of mobile homes located in East Clarke County is in an area with a moderately high Hispanic or Latinx population. Additionally, these populations are located mostly in Clarke County and not the surrounding areas. The cluster of mobile homes to the west also happens to be in an area with a moderately high Hispanic population. Due to mobile homes being more vulnerable to the impacts of tornados, and with a larger Hispanic and/or Latinx population, it can be determined that these populations are at a higher risk of the impacts of tornados.

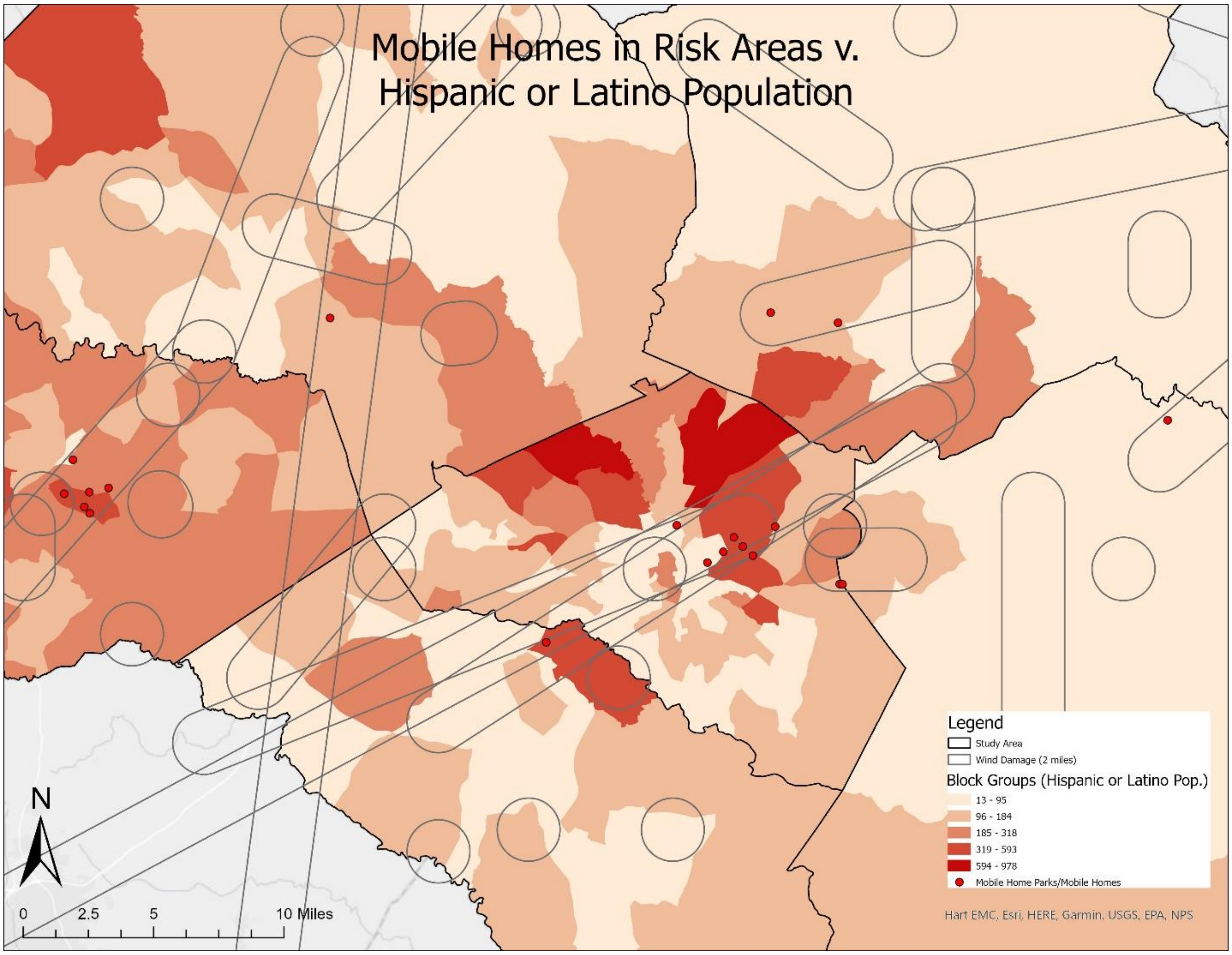


Figure 30- A map of mobile homes in risk areas vs. Hispanic and/or Latinx population.

The Black and African American Population distribution is similar to that of the Hispanic or Latinx populations. The history of redlining and segregation in the study area and more specifically, in Athens, is clearly seen in Figure 21. Much of the study area's Black population is located within Clarke County, and more specifically the Northeast block group. This is also where a large cluster of mobile homes is located.

It is important to note the spatial correlation between all four factors, (i.e., Black, White, Hispanic or Latinx and median household income) with mobile home park locations that resulted from the overlay and reselect functions of the MCDA modeling framework. When comparing income and location of mobile home parks, often times, lower income block groups are home to more mobile home parks. Minorities, including Black and Hispanic/Latinx populations are often underpaid, leading to lower household incomes. In the paper Decomposing the Wage Gap: Analysis of the Wage Gap Between Racial and Ethnic Minorities and Whites, it is shown that "empirical analysis of the Bureau of Labor Statistics March 2013 Current Population Survey (CPS) reveals that a statistically significant gap in hourly wages exists between Blacks and Hispanics in comparison to Whites" (Kamara 2015). Due to a lower household income, these underpaid minorities may look for less costly housing, including mobile homes. While tornadoes do not specifically target mobile home parks/mobile homes, these communities are in greater danger due to the fragility of the mobile homes themselves. Winds that a home with a foundation may withstand could destroy a mobile home. Therefore, those who live in mobile homes are disproportionately impacted by tornados.

CHAPTER 6

SUMMARY AND CONCLUSIONS

Deep learning is a growing field within academia, commercial, industrial and governmental sectors. It can be used to assess agriculture, architecture, and so much more. Many of its uses involve satellite imagery and remote sensing. Within this research, deep learning is used to identify mobile homes and mobile home parks within Clarke County. While this deep learning attempt had a 6% accuracy rate, many of the objects falsely detected had a similar shape and pattern to mobile homes, a rectangular and white shape, often arranged close together in regular rows. This indicates that the model does work on some level and can be further optimized and training samples added in order to properly recognize only mobile homes and mobile home parks. Like the study using deep learning to recognize Iranian courtyards by Yazdi et al. (2021), more training and validation samples could be used in the deep learning model to achieve a higher accuracy rate. While this research used approximately 100 samples, the Iranian architecture study used approximately 1000 samples of both "historical and non-historical houses," allowing the model having a variety of examples of courtyards to compare to instead of simply using one type of training sample (Yazdi et. al, 2021). Additionally, higher spatial resolution imagery, such as that from an unmanned aerial vehicle (UAV) could be beneficial. Furthermore, the UAV data could be taken during the winter, when foliage is less likely to obstruct training samples. In the case of detecting mobile homes, other categories of training sample could be created based on the inaccurate detections by the model. These would include parking lots with cars, chicken houses, and single-family homes. This would allow for a greater probability of classifying similar urban features and distinguishing between mobile homes and other rectangular, patterned objects.

Mobile home residents face the impacts of severe weather more than those who live in single-family homes made of more substantial materials with basements or attached to concrete slabs. Due to the structure of the mobile home itself, they are significantly more vulnerable to tornados, even those ranked as a 0 on the Enhanced Fujita scale. However, they are also an affordable housing option for those in lower income brackets. Mobile homes have "emerged as the housing choice among low- and moderate-income rural residents" establishing income as a vulnerability factor for severe weather (MacTavish 2007). While they are more vulnerable to severe weather, this is a risk many are willing to accept in order to have a roof over their head for a lower price than a single-family home or apartment, even in places such as Tornado Alley.

Race and Hispanic/Latinx origin also were shown to be factors for social vulnerability to severe weather. Due to a history of oppression and marginalizing of these communities, many Black and Hispanic or Latinx families and communities find themselves residing in mobile homes and mobile home parks. As illustrated in the maps provided above, and in a study of Texas mobile home parks by Sullivan et al. (2021), "as the share of land in [mobile home parks] increases, "higher shares of Hispanic/Latinx households and lower shares of non-Hispanic Black households" are prevalent within these block groups "compared to the region as a whole" (Sullivan 2021).

Due to time and computer constraints, deep learning was only performed on one county, Clarke, instead of the entire study area. In the future, it would be beneficial to make a mosaic of the entire study area or of a new study area and take additional training samples, approaching 1,000. It may also be beneficial to take samples in periods when vegetation is less prevalent, including the fall and winter. This would allow for more accurate detection by the deep learning model due to lack of obstruction. Higher resolution imagery, such as that from a drone, would provide clearer data for the deep learning model to work off of. Advancements in deep learning are coming in every day and will therefore be more accurate as time goes on. The Deep Learning Libraries for ArcGIS Pro 3.2 were used because updated libraries for ArcGIS Pro 3.3 were noted as coming, but not yet available as of the end of May/Early June 2024.

This research provides insight into whether or not mobile home parks can be detected and mapped using aerial imagery of high spatial resolution (i.e., 1-m NAIP images) and deep learning methods in ArcGIS Pro. While deep learning has been shown to recognize other relatively small human-built features, such as Iranian central courtyards, by introducing a new type of building infrastructure to the deep learning method, this research is expected to impact future applications related to the vulnerability of and services needed by residents of mobile home parks. Although the study area for the deep learning aspect of this research was limited to Clarke County, Georgia, the findings of this study will influence future research into whether mobile home parks can be recognized by remote sensing and deep learning in other parts of the country with varying terrain. Additionally, the demographic and vulnerability analysis will raise awareness as to which communities are disproportionately impacted by severe weather due to their residence. It is hoped that these results will be used to identify areas requiring special attention for disaster response during tornado seasons, early warning systems designed to reach more socially vulnerable populations and increased efforts to educate non-English speaking and lower income households on measures they can take to better protect their families from tornados.

REFERENCES

Aman, Destiny D., and Brent Yarnal, 2010. “Home Sweet Mobile Home? Benefits and Challenges of Mobile Home Ownership in Rural Pennsylvania.” *Applied Geography* vol. 30, no. 1: 84–95. https://doi.org/10.1016/j.apgeog.2009.09.001

Arnold, Caitlin R., "Locating Low Head Dams Using a Deep Learning Model in ArcGIS Pro With Aerial Imagery" (2023). All Graduate Theses and Dissertations, Spring 1920 to Summer 2023. 8756.

Ash, Kevin D., Michael J. Egnoto, Stephen M. Strader, Walker S. Ashley, David B. Roueche, Kim E. Klockow-McClain, David Caplen, and Maurya Dickerson, 2020. “Structural Forces: Perception and Vulnerability Factors for Tornado Sheltering within Mobile and Manufactured Housing in Alabama and Mississippi.” *Weather, Climate, and Society* vol. 12, no. 3: 453–72. https://doi.org/10.1175/wcas-d-19-0088.1

BCFP Data. “Manufactured-Housing Consumer Finance in the United States.” SSRN Electronic Journal, 2014, https://doi.org/10.2139/ssrn.3790711.

Brooks, Matthew M, and Tom Mueller, 2020. “Factors affecting mobile home prevalence in the United States: Poverty, natural amenities, and employment in natural resources.” Population, Space and Place vol. 26 no. 4: 1-13. https://doi.org/10.1002/psp.2311

Castagno, Jeremy, and Ella Atkins, 2018. “Roof Shape Classification from Lidar and Satellite Image Data Fusion Using Supervised Learning.” *Sensors* vol. 18, no. 11: 3960. https://doi.org/10.3390/s18113960

CDC, 2003. “Staying Safe in a Tornado.” Centers for Disease Control and Prevention, April 3, 2023. Last accessed October 29, 2024. https://www.cdc.gov/nceh/features/tornadosafety/index.html

Cheng, Gong, and Junwei Han, 2016. “A Survey on Object Detection in Optical Remote Sensing Images.” *ISPRS Journal of Photogrammetry and Remote Sensing* 117: 11–28. https://doi.org/10.1016/j.isprsjprs.2016.03.014.

Cresson, Rémi, 2020. *Deep Learning for Remote Sensing Images with Open Source Software*, CRC Press, Boca Raton, Florida, 164 p. https://doi.org/10.1201/9781003020851

Crichton, David, 1999. The Risk Triangle, In, Ingelton, J., Ed. *Natural Disaster Management*, Tudor Rose, London, pp. 102-103.

ESRI. “Introduction to Deep Learning.” Introduction to Deep Learning-ArcGIS Pro | Documentation, pro.arcgis.com/en/pro-app/latest/help/analysis/deep-learning/what-is-deep-learning-.htm. Accessed 3 Nov. 2024.

FEMA. “Guide for All-Hazard Emergency Operations Planning.” Sept. 1996.

Fischetti, Mark, et al. “Watch out: Tornado Alley Is Migrating Eastward.” Scientific American, Scientific American, 20 Feb. 2024, www.scientificamerican.com/article/watch-out-tornado-alley-is-migrating-eastward/.

George, Lance, 2016. “Manufactured Housing.” National Low Income Housing Coalition.” Chapter 6, *Advocates' Guide*, 10 p., Last accessed October 29, 2024. https://nlihc.org/sites/default/files/2016AG_Chapter6-3.pdf

Goodfellow, Ian, Yoshua Bengio, and Aaron Courville, 2016. *Deep Learning*, MIT Press, Cambridge, Massachusetts, 781 p. https://www.deeplearningbook.org/

Huang, Fenghua, Ying Yu, and Tinghao Feng, 2019. “Automatic Extraction of Urban Impervious Surfaces Based on Deep Learning and Multi-Source Remote Sensing Data.” *Journal of Visual Communication and Image Representation* vol. 60 : 16–27. https://doi.org/10.1016/j.jvcir.2018.12.051

Ibrahim, Mostafa. “A Deep Dive into Learning Curves in Machine Learning.” W&B, 9 June 2023, wandb.ai/mostafaibrahim17/ml-articles/reports/A-Deep-Dive-Into-Learning-Curves-in-Machine-Learning--Vmlldzo0NjA1ODY0.

Ienco, Dino, Raffaele Gaetano, Claire Dupaquier, and Pierre Maurel, 2017. “Land Cover Classification via Multitemporal Spatial Data by Deep Recurrent Neural Networks.” *IEEE Geoscience and Remote Sensing Letters* vol. 14, no. 10: 1685–89. https://doi.org/10.1109/lgrs.2017.2728698

“Introduction to Deep Learning.” Introduction to Deep Learning-ArcGIS Pro | Documentation, pro.arcgis.com/en/pro-app/latest/help/analysis/deep-learning/what-is-deep-learning-.htm.

IPUMS NHGIS, 2024. Integrated Public Use Microdata Series (IPUMS) National Historical Geographic Information System (NHGIS)Last accessed October 20, 2024. https://www.nhgis.org

Jackson, Candace, 2021. “What Is Redlining?” *The New York Times*, August 17, 2021. https://www.nytimes.com/2021/08/17/realestate/what-is-redlining.html

Kamara, Jennifer, 2015. "Decomposing the Wage Gap: Analysis of the Wage Gap Between Racial and Ethnic Minorities and Whites," *Pepperdine Policy Review,* vol. 8, Article 1. https://digital commons.pepperdine.edu/ppr/vol8/iss1/1

"Libguides: Planet Labs Satellite Imagery: Home," 2024. Home - Planet Labs Satellite Imagery - LibGuides at Brown University, libguides.brown.edu/planet.

Lillesand, T., Kiefer, R.W. and J. Chipman, 2015. *Remote Sensing and Image Interpretation*, 7th Edition, John Wiley & Sons, New York, 736 p.

Lunga, Dalton, Matthew Seals and Budhendra Bhaduri, 2018. Multilevel semantic labeling of mobile homes from overhead imagery. IEEE International Geoscience and Remote Sensing Symposium (IGARSS) Conference Proceedings, Valencia, Spain, July 22-27, 2018. https://ieeexplore.ieee.org/document/8517660/

MacTavish, Katherine A, 2007. "The wrong side of the tracks: Social Inequality and mobile home park residence." Community Development, vol. 38, no. 1: 74–91. https://doi.org/10.1080/15575330709490186

Maggiori, Emmanuel, Yuliya Tarabalka, Guillaume Charpiat, and Pierre Alliez, 2017. "Convolutional Neural Networks for Large-Scale Remote-Sensing Image Classification." *IEEE Transactions on Geoscience and Remote Sensing*, vol. 55, no. 2: 645–57. https://doi.org/10.1109/tgrs.2016.2612821

Manson, Steven et al. IPUMS National Historical Geographic Information System: Version 19.0. Minneapolis, MN: IPUMS. 2024. http://doi.org/10.18128/D050.V19.0

NOAA, 2023. "Tornado Basics." NOAA National Severe Storms Laboratory. Last accessed October 29, 2024. https://www.nssl.noaa.gov/education/svrwx101/tornadoes/

NOAA, 2023. "Tornado Tracks." FEMA Geospatial Resource Center, gis-fema.hub.arcgis.com/datasets/fedmaps::tornado-tracks-1/about.

NWS, 2024. "Yearly Climate Graphs for Atlanta, Athens, Columbus and Macon, GA", National Weather Service (NWS), National Oceanic and Atmospheric Administration, Last accessed October 29, 2024, https://www.weather.gov/ffc/climateplot

Oak Ridge National Laboratory. "Mobile Home Parks." Sept. 2018. https://www.arcgis.com/home/item.html?id=4c659dcf93bc447e9fa2ca5b3fb71ee2

Ryan, Siobhan, and Ellis Nimick, 2019. "Multi-Criteria Decision Analysis and GIS." ArcGIS StoryMaps, August 11, 2019. https://storymaps.arcgis.com/stories/b60b7399f6944bca86d1be6616c178cf

Shivers-Williams, Cassandra A., and Daphne S. LaDue, 2022. "Exploring southeast US mobile and manufactured home residents' anchoring decisions." *International Journal of Disaster Risk Reduction*, vol. 82, p. 103383, https://doi.org/10.1016/j.ijdrr.2022.103383

Strader, Stephen M., Kevin Ash, Eric Wagner, and Chayla Sherrod, 2019. "Mobile Home Resident Evacuation Vulnerability and Emergency Medical Service Access during Tornado Events in the Southeast United States." *International Journal of Disaster Risk Reduction* vol. 38: 101210. https://doi.org/10.1016/j.ijdrr.2019.101210.

Sullivan, Esther, Carrie Makarewicz, and Andrew Rumbach, 2021. "Affordable but Marginalized." *Journal of the American Planning Association* vol. 88, no. 2: 232–44. https://doi.org/10.1080/01944363.2021.1952477

U.S. Census Bureau, 1994. *Geographic Areas Reference Manual*. U.S. Dept. of Commerce, Economics and Statistics Administration, Bureau of the Census. Last accessed October 29, 2024. https://www2.census.gov/geo/pdfs/reference/GARM/GARMcont.pdf

U.S. Census, 2024. "American Community Survey (ACS)." Census.Gov, 26 Sept. 2024, Last accessed October 29, 2024, www.census.gov/programs-surveys/acs

USDA, 2024. USDA NAIP GeoHub, National Agricultural Imagery Program (NAIP), U.S. Department of Agriculture, Last accessed October 29, 2024. https://naip-usdaonline.hub.arcgis.com

"USGS Eros Archive - Aerial Photography - National Agriculture Imagery Program (NAIP)." USGS EROS Archive - Aerial Photography - National Agriculture Imagery Program (NAIP) | U.S. Geological Survey, www.usgs.gov/centers/eros/science/usgs-eros-archive-aerial-photography-national-agriculture-imagery-program-naip.

Waller, Margy, 2005 "High Cost or High Opportunity Cost? Transportation and Family Economic Success." *The Brookings Institution Policy Brief*, Washington, D.C., 8 p. https://www.academia.edu/61313790/High_Cost_or_High_Opportunity_Cost_Transportation_and_Family_Economic_Success

Yazdi, Hadi, Ilija Vukorep, Marzena Banach, Sajad Moazen, Adam Nadolny, Rolf Starke, and Hassan Bazazzadeh, 2021. "Central Courtyard Feature Extraction in Remote Sensing Aerial Images Using Deep Learning: A Case-Study of Iran." *Remote Sensing* vol. 13, no. 23: 4843. https://doi.org/10.3390/rs13234843

Yen, Kin Sam, and Hui Liu, 2024. "A review of advancements in deep learning-based shadow detection and removal in image and video analysis." *International Journal of Intelligent Engineering Informatics*, vol. 12, no. 2, https://doi.org/10.1504/ijiei.2024.10062950

Youssef, Rissouni, Moumen Aniss, and Chao Jamal, 2020. "Machine Learning and Deep Learning in Remote Sensing and Urban Application." *Proceedings of the 4th Edition of International Conference on Geo-IT and Water Resources 2020, Geo-IT and Water Resources 2020*, March 11, 2020. https://doi.org/10.1145/3399205.3399224