Spatial disparities in air conditioning ownership in Florida, United States

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ABSTRACT

This study emphasizes the critical role of air conditioning (AC) in preventing heat-related illnesses such as heat exhaustion and heatstroke. The challenge of limited geographic coverage and outdated AC availability data hampers effective heat risk mapping and prevention efforts. We identified areas with significant AC needs and examined factors related to AC ownership in Florida, U.S. Local Indicators of Spatial Association results displayed distinct AC ownership disparities, with high-high clusters in coastal and metropolitan areas and AC-deficient clusters inland. Vulnerable urban communities, predominantly inhabited by marginalized groups, had limited to no AC availability. The Spatial Durbin Model results revealed a significant correlation between AC ownership and socioeconomic and urban factors. Notably, a higher proportion of AC-deficient households were in predominantly African-American neighborhoods, underscoring racial disparities in AC ownership. These findings provide valuable insights for targeted interventions to mitigate heat-related risks and adapt to evolving climate conditions in vulnerable neighborhoods.

Key policy highlights

- This study evaluated the ability of real estate records to generate neighborhood-level AC data
- This study visualized and identified areas of AC disparities to inform future policy and adaptation actions.

1. Introduction

Extreme heat exposure can cause heat-related illness and exacerbate respiratory, cardiovascular, and renal disease (Dahl et al., 2019). Disparities of heat exposure and sensitivities are influenced by environmental conditions and social and economic status (Kuras et al., 2017; Seema G. Nayak et al., 2017; Ziegler et al., 2019). Extreme heat is an environmental justice concern: the highest mortality and morbidity rates associated with extreme heat occur disproportionately upon socially and economically marginalized groups such as older adults, people with low-income, and racialized minorities (Centers for Disease Control and Prevention, 2020; Harlan et al., 2006; Kuras et al., 2017). Studies show that disadvantaged populations, such as people of color, specifically low-income impoverished African Americans, living in urban areas, might be at higher risks due to limited access to resources, economic duress, and hotter living environments (e.g. White-Newsome et al., 2009; Wilson et al., 2010). Moreover, people living in indoor environments with inadequate climate controls and neighborhoods with less greenspace also face elevated heat exposures and heat risk (Gabbe & Pierce, 2020; Kuras et al., 2017; Madrigan et al., 2015; Ziegler et al., 2019).

Ensuring equitable access to cooling infrastructure (e.g. household air conditioning) can be one of the most important strategies to prevent heat-related illnesses and redress historic heat exposure disparities (Ito et al., 2018). This effort dovetails with broader infrastructure, racial capitalism, economic and energy justice movements (Hernández et al., 2021; Maxim & Grubert, 2021; Ponder, 2021; Purifoy & Seamster, 2021). A large and growing body of literature has investigated factors influencing heat exposure in indoor environments. More specifically, many studies have focused on the temperature difference between the indoors and outdoors according to air

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conditioning (AC) availability (Quinn et al., 2017; Quinn et al., 2014; Waugh et al., 2021). Waugh et al. (2021) found that daily mean indoor air temperature varies from 10 °C lower to 10 °C higher than the outdoor temperature. Quinn et al. (2017) discovered indoor temperatures are highly associated with cooling system types.

Furthermore, studies have linked limited AC ownership to higher rates of negative heat-related health effects. Several studies confirmed an inverse relationship between mortality rates and AC ownership (Cardoza et al., 2020; O’Neill et al., 2005; Ostro et al., 2010; Semenza et al., 1996). Additionally, some research highlights the racialized dynamics related to accessing AC, wherein marginalized groups were found to have less access to AC. O’Neill et al. (2005) discovered Black/African American households have less AC prevalence. Biddle (2008) also found that the association of lower central AC ownership is associated with higher household income elasticity and non-white families.

An association between AC ownership and residential building characteristics has been suggested in the literature (Barcus, 2016; Biddle, 2008; Gronlund & Berrocal, 2020; O’Neill et al., 2005). Nayak et al. (2018) found a strong relationship between AC prevalence and year of construction. Vant-Hull et al. (2018) suggested that the property’s value and total square footage negatively affect AC ownership, while Gronlund and Berrocal (2020) showed that newer houses tended to have an AC unit, and year of construction was a strong predictor.

Compounding environmental factors and historical policies related to property ownership might be related to ongoing gaps in access to resources and AC ownership. ‘Redlining,’ or historic disinvestment in neighborhoods with historically high proportions of foreign-born populations, is related to contemporary health inequalities and lacking access to resources (e.g., health care facilities, green space) that can improve overall health and well-being (Nardone et al., 2021; Schell et al., 2020).

Level of urbanity is also often used to measure access to resources and health status. Urbanity is also often used to measure access to resources and health status. Kovach et al. (2015) found more Emergency Department visits from rural areas than urban areas in North Carolina in the US, and these tended to be elderly, socially isolated, noncitizens, agricultural laborers, and mobile home residents who are unable to avoid the heat.

The 1980 US Decennial Census was the last nationwide survey to examine neighborhood-level central AC prevalence across the US. Thus, studies applying heat mapping methods to identify disparities and target health interventions have been hampered by limited AC prevalence information (Ahn & Uejio, 2022; Gabbe & Pierce, 2020; S. G. Nayak et al., 2018; Reid et al., 2009; Uejio et al., 2011). Outdated information on AC prevalence constrains the optimal targeting of interventions such as cooling refuges, energy subsidies, and free AC distribution. A few studies incorporated AC information from the US Census Bureau’s American Housing Survey (AHS). However, the data from AHS is only available at the city level for selected metropolitan areas. In the absence of a nationwide census, real estate companies, which collect high-quality property information, could provide reliable AC prevalence information.

As areas all over the world experience more extreme and frequent heat waves, it becomes increasingly important to analyze high-quality, current data on cooling infrastructure in order to identify the most vulnerable populations and implement timely interventions. This study incorporated the real estate data from ‘Estated,’ a private real estate company that provided rich information about properties’ characteristics, including AC ownership, to overcome the limited census data availability.

Numerous studies applied various methods to detect disparities. Common methods include simple comparisons between subgroups (highest group versus lowest group prevalence) (Cheng et al., 2008), relative or absolute disparity indices or thresholds (Harper et al., 2021; Liu et al., 2021), spatial and aspatial regression analysis (Pedigo et al., 2011; Sin, 2011; Wong et al., 2023), and Local Indicators of Spatial Association (LISA) (Bokhari & Sharifi, 2023; Yourkavitch et al., 2018). Among the methods, the study chose LISA since it explicitly considers spatial spatial heterogeneity and disparities and is widely used. For example, Yourkavitch et al. (2018) applied LISA to find areas with a high proportion of people at risk of cancer and geographic inequities in healthcare facilities. Bokhari and Sharifi (2023) examined spatial disparities of urban amenities (transportation, green space, and health care), which are often related to the well-being of older adult populations.

To detect spatial disparities in AC ownership, LISA was used. By using high spatial resolution real estate data and LISA to identify spatial clusters of AC prevalence in Florida as a case study, this study reveals the areas with the most significant AC needs. This study also investigates the relationships between AC ownership and socioeconomic variables with Spatial Durbin Model (SDM). In doing so, this paper draws attention to a useful data source for AC information and generates new empirical insights on one of the states most vulnerable to extreme heat in the U.S.

2. Materials and methods

2.1. Study site

Hotter and more humid air masses influence subtropical and tropical climate areas more than other climates
indoor overheating (Baniassadi et al., 2019). In Florida, statewide average summer temperatures exceed 30 degrees Celsius (86 degrees Fahrenheit), and some residents lack AC units to manage and cool indoor environments. According to the AHS, in 1980, 16% of Florida households had no AC, 55% of households had central AC, 17% had one individual room unit, and 10% of houses had two or more individual room units. Without adequate updated information on AC prevalence, heat-related planning, and adaptation interventions are unlikely to address the actual and disproportionate heat-related health risks across communities or target households most at risk during extreme heat events. Therefore, this study investigated residential AC availability at the census tract level in Florida with records through 2019 using a novel real estate dataset to reflect more current/updated estimates of AC prevalence.

2.2. Data

2.2.1. Property data

‘Estated,’ which has access to more than 150 million properties nationwide, provided housing information for this study (Estated, 2021). The dataset includes detailed information on individual properties, including building structure, market value, taxes and assessment, and historical deeds. The dataset included a total of 72,954,014 residential properties in Florida. We excluded the properties that were missing either the year of construction or AC types, which left 42,679,440 (58.50%) properties for the analysis. Collier County, Putnam County, Sumter County, and Union County had no records of AC ownership. The top three counties with the most missing data on AC ownership were Miami-Dade County (99.5%), Polk County (99.4%), and Leon County (99.3%) (Table 2).

We referred to previous studies that investigated the association between AC ownership and socioeconomic characteristics to identify socioeconomic variables to link to AC ownership in this study (Barcus, 2016; Biddle, 2008; Gronlund and Berrocal, 2020; O’Neill et al., 2005). We collected ten variables such as property value, renter-occupied households, and complete plumbing from the 5-year American Community Survey (ACS) (Cheng et al., 2008) at the census tract level. In Florida, this sample includes approximately 3.54 million housing units.

2.2.2. Contemporary socioeconomic variables

Intuitively, AC ownership and use are related to residents’ socioeconomic position. Biddle (2008) investigated the growth of AC prevalence with historical census data and showed that AC ownership doubled in the 1980s compared to the 1960s due to the development of affordable AC units, declining cost of electricity, increasing household incomes, and new housing developments. O’Neill et al. (2005) mentioned the association between lower AC ownership and African American households.

Gronlund and Berrocal (2020) found that a proportion of rental homes had lower rates of central AC. We included the following socioeconomic variables based on these previous findings: households with no vehicles, over 65 living alone, citizenship status, below poverty, number Hispanic, number Black and African American, construction workers, linguistically isolated, immigration population, agriculture workers, number of vacant housings, and education level (high school).

2.2.3. Historic sociodemographic variables

Historical development and neighborhood characteristics may also influence building amenities such as AC availability (Hillier, 2003). Since historic redlining information is only available for three cities in Florida, we included census tract-level Black/African American population from the U.S. 1970 decennial census (IPUMS NHGIS, 1970). NHGIS provides polygon features that have matched historical census tract information with contemporary census tract codes. We used the code to match the historical Black/African American population information to the 2019 census tract boundary. This date follows the passage of the 1968 Fair Housing Act and likely contains vestiges of past discriminatory practices.

2.2.4. Urbanicity variable

The physical environment and social context shape health and well-being. Urbanicity often represents the availability of facilities (e.g. health care, cooling centers, and fitness centers) related to health and well-being (U.S. Department of Health and Human Services, 2023). For example, rural areas tended to have less investment and low housing quality directly related to household appliances (e.g. AC, heating systems, kitchen stoves, water heaters) ownership and residential environment (Newman & Holupka, 2017). The United States Department of Agriculture (USDA) (2013) classifies census tracts into 11 urban and rural subtypes based on population density, urbanization, and commuting patterns. This study collapsed the ten original urban/rural codes into four classes, as follows: Metro Urbanized Areas (UAs) (Metropolitan area core UA, Metropolitan area high commuting UA, Metropolitan area low commuting UA), Metro Urban Clusters (UCs) Micropolitan area core large UC, Micropolitan high commuting large UC, Micropolitan low commuting large UC), Town UC (Small-town core small UC, Small-town high commuting small UC, Small-town low commuting small UC), and Rural (outside a UA or UC).
We extracted the year of construction, total property square footage, and AC types from the Estated dataset and aggregated the AC dataset with the mean value of the census tract. The Estated dataset provided information on individual properties’ AC types, including central, chilled water, evaporative cooler, geothermal, packaged AC unit, partial, refrigeration, ventilation, wall unit, window unit, yes, none, and others. Some studies have found differential cooling effectiveness among various AC types (Quinn et al., 2017; Waugh et al., 2021). Waugh et al. (2021) indicate that houses with room AC units had a higher indoor temperature of 2 degrees Celsius on average than houses with central AC. Further, Quinn et al. (2017) suggested that a portable AC was closer to not having an AC than to central AC based on room temperature.

Some jurisdictions only reported the presence or absence of AC which constrained the statewide analysis of residential AC types. Thus, the study grouped AC into three: any AC (packaged AC unit, chilled

**Table 1.** Data summary.

| Characteristic (unit) | Mean (SD) at the census tract level | Data source (year) |
|-----------------------|------------------------------------|-------------------|
| Over 65 lives alone (count) | 202 (180) | ACS (2019) |
| Black or African American (count) | 655 (971) | ACS (2019) |
| Renter occupied (count) | 1,368 (1,115) | ACS (2019) |
| Hispanic or Latino (count) | 1,060 (1,212) | ACS (2019) |
| Median household income (dollar) | 255,177 (174,335) | ACS (2019) |
| Number of rooms (count) | 5.33 (0.96) | ACS (2019) |
| Complete plumbing (count) | 1,837 (833) | ACS (2019) |
| Median housing value (dollar) | 62,473 (27,652) | ACS (2019) |

**Socioeconomic Characteristics**

| Characteristics (unit) | Mean (SD) at the census tract level | Data source (year) |
|-----------------------|------------------------------------|-------------------|
| Year built (year) | 1,984 (21) | Estated |
| Total area (sq ft) | 1,840 (3,269) | Estated |
| Year built (year) | 1,984 (21) | Estated |

**Historical Demographic Characteristics**

| Characteristics (count) | Mean (SD) at the census tract level | Data source (year) |
|-----------------------|------------------------------------|-------------------|
| Black or African American (count) | 392 (865) | NHGIS (1970) |

**Property Characteristics**

| Characteristics (count) | Mean (SD or percentage for categorical variables) | Data source (year) |
|------------------------|--------------------------------------------------|-------------------|
| AnyAC Central (count) | 30,424,552 (71%) | Estated (2021) |
| Chilled water (count) | 3,199 (<0.1%) | Estated (2021) |
| Evaporative cooler (count) | 651 (<0.1%) | Estated (2021) |
| Geothermal (count) | 1,524 (<0.1%) | Estated (2021) |
| Other (count) | 20,137 (<0.1%) | Estated (2021) |
| Packaged unit (count) | 831,942 (1.9%) | Estated (2021) |
| Rooftop packaged unit (count) | 226 (<0.1%) | Estated (2021) |
| Ventilation (count) | 538 (<0.1%) | Estated (2021) |
| Wall (count) | 161,429 (0.4%) | Estated (2021) |
| Window unit (count) | 288,187 (0.7%) | Estated (2021) |
| Yes (count) | 10,246,944 (24%) | Estated (2021) |
| NoAC None (count) | 700,091 (1.6%) | Estated (2021) |
| Total area (sq ft) | 1,840 (3,269) | Estated (2021) |
| Year built (year) | 1,984 (21) | Estated (2021) |

**Table 2. Percentage of AC records by county.**

| County                  | Central and others | No | NA |
|-------------------------|--------------------|----|----|
| Alachua County          | 91.88              | 3.31 | 4.81 |
| Baker County            | 92.86              | 1.75 | 5.39 |
| Bay County              | 77.44              | 0.65 | 15.71 |
| Bradford County         | 87.87              | 8.77 | 2.73 |
| Brevard County          | 77.24              | 1.55 | 21.21 |
| Broward County          | 51.57              | NA  | 48.43 |
| Calhoun County          | 83.32              | 6.04 | 10.64 |
| Charlotte County        | 48.67              | NA  | 51.33 |
| Citrus County           | 80.78              | 2.53 | 16.69 |
| Clay County             | 88.66              | 3.41 | 7.99 |
| Collier County          | NA                 | NA  | 100 |
| Columbia County         | 93.17              | 2.07 | 4.76 |
| DeSoto County           | 89.9               | 3.35 | 6.75 |
| Dixie County            | 68.09              | NA  | 31.91 |
| Duval County            | 89.01              | 0.65 | 10.34 |
| Escambia County         | 83.45              | 0.26 | 16.29 |
| Flagler County          | 77.97              | 0.17 | 17.21 |
| Franklin County         | 71.54              | 10.48 | 17.97 |
| Gadsden County          | 89.67              | 4.8  | 5.53 |
| Gilchrist County        | 86.26              | 5.05 | 8.69 |
| Glades County           | 77.97              | 3.58 | 18.45 |
| Gulf County             | 83.11              | 5.4  | 11.49 |
| Hamilton County         | 66.56              | 14.61 | 18.83 |
| Hardee County           | 89.7              | 0.91 | 9.4  |
| Hendry County           | 74.07              | 9.07 | 16.86 |
| Hernando County         | 88.26              | NA  | 11.74 |
| Highlands County        | 83.98              | 8.01 | 8.09 |
| Hillsborough County     | 95.73              | 0.67 | 3.6  |
| Holmes County           | 77.87              | 1.55 | 20.58 |
| Indian River County     | 66.74              | NA  | 33.26 |
| Jackson County          | 85.56              | 8.61 | 5.82 |
| Jefferson County        | 79.09              | 7.34 | 15.57 |
| Lafayette County        | 79.58              | 0.15 | 20.26 |
| Lake County             | 87.43              | NA  | 12.57 |
| Lee County              | 74.48              | 0.26 | 25.26 |
| Leon County             | 0.68               | NA  | 99.32 |
| Levy County             | 83.01              | NA  | 14.99 |
| Liberty County          | 76.98              | 14.29 | 8.73 |
| Madison County          | 82.29              | NA  | 17.71 |
| Manatee County          | 85.3              | 0.01 | 14.7 |
| Marion County           | 90.03              | NA  | 9.97 |
| Martin County           | 95.16              | NA  | 4.84 |
| Miami-Dade County       | 0.46               | NA  | 99.54 |
| Monroe County           | 54.77              | 16.57 | 28.66 |
| Nassau County           | 80.48              | 2.94 | 15.68 |
| Okaloosa County         | 78.1              | 1.53 | 20.37 |
| Okeechobee County       | 76.38              | 11.03 | 12.59 |
| Orange County           | 96.32              | 1.31 | 2.37 |
| Osceola County          | 94.53              | NA  | 5.47 |
| Palm Beach County       | 42.19              | 2.32 | 55.5 |
| Pasco County            | 78.8               | 0.96 | 20.25 |
| Pinellas County         | 65.45              | 3.92 | 30.63 |
| Polk County             | 0.59               | NA  | 99.41 |
| Putnam County           | NA                 | NA  | 100 |
| St. Johns County        | 75.31              | 0.48 | 24.22 |
| St. Lucie County        | 76.45              | NA  | 23.53 |
| Santa Rosa County       | 91.4              | 0.06 | 8.44 |
| Sarasota County         | 93.92              | 0.43 | 5.65 |
| Seminole County         | 87.36              | 0.03 | 12.61 |
| Sumter County           | NA                 | NA  | 100 |
| Suwannee County         | 90.79              | NA  | 9.21 |
| Taylor County           | 89.33              | 3.26 | 7.4  |
| Union County            | NA                 | NA  | 100 |
| Volusia County          | 81.28              | 2.73 | 15.99 |
| Wakulla County          | 91.52              | 1.11 | 7.38 |
| Walton County           | 77.84              | 1.43 | 20.73 |
| Washington County       | 67.06              | 2.07 | 30.87 |
water, geothermal, commercial unit, central AC, wall unit, window unit, evaporative cooler, and other AC unit), no AC (none and ventilation), and missing data. The study presumed that areas with 100% AC automatically had no households without AC since there were residences with missing AC information across the study area. Next, we calculated the percentage of each AC type at the census tract level by dividing it by the total number of units reporting AC availability.

We calculated the percentage of renter-occupied and the percent of households with complete plumbing facilities divided by the number of total housing units. The contemporary socioeconomic variables were converted to the proportion of the population (Table 1). We calculated the percent of Black and African American population from the historic total population and Black African American and matched it with the contemporary census tract.

To compare the effect of each variable on the dependent variable, we standardized all variables by converting them to Z-scores (subtracting the mean and dividing by the standard deviation). We standardized to avoid over-emphasizing one variable’s effect on the dependent variable.

### 2.4. Statistical analysis

The analysis was conducted at the census tract level of data. This analysis aimed to identify the spatial autocorrelation of AC availability in Florida. We separately applied Moran’s I test to the percentage of census tracts with anyAC and noAC using the ‘spdep’ package in R (Luc Anselin, 1995) to examine spatial autocorrelation in Florida. Moran’s I statistic is a global spatial autocorrelation statistic designed to test the null hypothesis of complete spatial randomness. To conduct Moran’s I statistic test, we defined the neighborhood of census tract polygons with the queen criterion of contiguity. We applied a binary weights matrix without row standardization, which gives more weight to areas with more neighbors.

Among the total of 5,160 census tracts from 67 counties in Florida, some census tracts contained missing values. We included 4,066 census tracts from 63 counties for anyAC and 2,505 census tracts from 47 counties for the noAC analysis. Due to missing data, the study did not presume that neighborhoods with 100% AC prevalence meant that every household in that neighborhood had some type of AC.

We applied Local Indicators of Spatial Association (LISA) to AC availability in Florida with the ‘spdep’ package in R version 4.1.1 (Luc Anselin, 1995). We operationalized neighborhoods using queen contiguity without row standardization to conduct LISA analysis. The sub-analysis reports specific information for Duval County.

To consider potential multicollinearity between independent variables, we retained explanatory variables when the Variance Inflation (VIF) was less than 5. The percentage of households without AC was the dependent variable. The rest were independent variables which are listed in Table 1. We excluded the following independent variables from the model due to high VIF values: the proportion of no vehicles, the proportion of noncitizens, construction workers, linguistically isolated, agriculture workers, and the proportion of vacant housings from the model.

Spatial error (SEM) and spatial lag model (SLM) are commonly applied to handle residual autocorrelation (Gabbe & Pierce, 2020). The SLM can be used for a diffusion process that looks at how one event increases the likelihood of similar events in neighboring areas (Moraga, 2019).

SEM treats spatial dependence as a nuisance. In other words, SEM controls for the unexplained autocorrelation by adding a spatial residual term as an independent variable (Paynich & Hill, 2011). However, some studies suggested that applying either SEM or SLM can lead to erroneous conclusions (Elhorst, 2010; LeSage & Pace, 2009). For example, the SLM model cannot account for spatial correlation in the error term. SEM cannot provide information about the indirect effects of neighbors (LeSage & Pace, 2009). To capture both error dependence and spatially lagged dependence, we applied the Spatial Durbin Model (SDM) (L. Anselin et al., 1996; LeSage & Pace, 2009). The SDM is considered more robust since it considers both local and global spatial effects with no prior restrictions on the magnitude of potential direct and indirect effects (Elhorst, 2010).

SDM provides direct effect and indirect independent variable effect estimates. The direct effect refers to the changes of dependent variable effects on a census tract, and this also considers how census tract changes affect its neighboring census tract (LeSage & Pace, 2009). The indirect effect or spatial spillover effect refers to the neighboring dependent variable’s impact on their census tracts’ dependent variable, while the total effect sums the direct and indirect effects (LeSage & Pace, 2009). The results report the standardized beta coefficients (one standard deviation change), 95% confidence intervals, and p-values.

### 3. Results

#### 3.1. Descriptive statistics

A summary of AC ownership is provided in Table 1. According to the summary, 30,424,552 (71%) of houses have central AC, 10,246,944 (24%) of houses indicated Yes to AC, 21,922 (1%) of houses have other types of AC, and 700,091 (1.6%) households had no AC (Table 1). Among the 67 counties in
Florida, AC data were not available in four counties (Collier County, Putnam County, Sumter County, and Union County). There were some counties with a high percentage of no AC, including Monroe County (16.5%), Liberty County (14.2%), Hamilton County (14.6%), Okeechobee County (11.0%), and Franklin County (10.4%) (Table 2).

### 3.2. Spatial clusters in Florida

We conducted spatial autocorrelation analysis to identify the areas with high and low AC prevalence at the census tract level. Moran’s I statistics and the LISA maps (Figure 1) confirmed the spatial autocorrelation of AC availability. Any type of AC exhibited strong and statistically significant spatial autocorrelation (Moran I statistic 0.74, \( p < 0.05 \)). A high AC prevalence neighborhood geographically adjacent to another high AC prevalence area was found in 204 census tracts. High-High clusters were found in Duval County, Marion County, Lee County, Lake County, Sarasota County, Pasco County, Pinellas County, Broward County, Manatee County, St. Johns County, Okaloosa County, Clay County, Volusia County, and Bay County (Map Map 1). A low AC prevalence neighborhood was geographically adjacent to another low AC prevalence area in 238 census tracts. Low-Low clusters were found in Leon County, Polk County, and Miami-Dade County. A low proportion of neighborhoods with any type of AC, referred to as a Low-High cluster, was found in 13 census tracts spanning the following counties: Sarasota, Duval, Okaloosa, Broward, Walton, Marion, and Volusia (Map Map 1). There were no High-Low clusters.

No AC census tracts also showed statistically significant spatial autocorrelation (Moran I statistic 0.75, \( p < 0.05 \)). A high proportion of neighborhoods without AC geographically adjacent to another high proportion of areas without AC were found in 188 census tracts. These High-High clusters were in Pinellas County, Volusia County, Alachua County, Orange County, Okeechobee County, Monroe County, Clay County, and Palm Beach County (Map Map 2). A low proportion of neighborhoods without AC geographically adjacent to a high proportion of areas without AC was found in 4 census tracts. These Low-High clusters were found in Alachua County, Palm Beach County, and Pinellas County (Map Map 2).

### 3.3. Relationship between AC availability and socioeconomic variables

Several socioeconomic variables showed statistically significant associations with the percentage of areas without AC. Table 3 reports the effect with tree matrices: direct, indirect, and total. We discovered that the percent of Black and African Americans showed a positive relationship with lack of AC ownership in direct (0.01, 95% CI: 0, 0.01), indirect (0, 95% CI: 0, 0), and total effects (0.01, 95% CI: 0, 0.01). People living in historically Black/African American (1970 Census) areas with lower housing quality were less likely to have any type of AC (direct (0.01, 95% CI: 0, 0.01), indirect (0, 95% CI: 0, 0), and total effects (0.01, 95% CI: 0, 0.01).
Many of the residential property features were significantly associated with no AC. The average number of rooms per residence (i.e. size of household) was negatively related to a percentage of households without AC across all effect categories: direct impact (−0.01, 95% CI: −0.01,0), indirect (0. 95% CI: −0.01,0), and total effects (−0.02, 95% CI: −0.02,0). Older houses tend not to have any AC units. Thus, the year of construction was also negatively associated with the percentage of households without AC in direct effect (−0.01, 95% CI:−0.02,−0.01) and total effect (−0.06, 95% CI:−0.1,−0.03). Metro Clusters showed the largest effect of all variables of direct effect 0.15 (95% CI:0.10,0.19), indirect effect (0.04, 95% CI:0.00,0.07), and total effect 0.18 (95% CI:0.12,0.25) with the percentage of property without AC. Rural Clusters also showed a statistically significant direct effect (0.3, 95% CI:0.25,0.35) and total effect (0.39, 95% CI:0.31,0.47) (Table 3).

### 4. Discussion

AC availability can considerably vary within a state and a county (Barcus, 2016; Biddle, 2008; Gronlund & Berrocal, 2020; O’Neill et al., 2005). The results from the LISA analysis identified a significant number of spatial clusters of AC ownership in Florida that can be used to provide resources for heat prevention, such as supplying AC units, installing cooling centers, and distributing energy subsidies. This study found clusters of households without any AC in Hillsborough, Palm Beach, Alachua, Volusia, and Orange Counties. The areas with a high percentage of not having AC tended to align with a high concentration of poverty and minority population (Harper et al., 2021; Palm Beach County, 2019; Pinellas County, 2023). This result illustrates that AC ownership is likely to be associated with socioeconomic variables and disproportionate health outcomes.

We applied a SDM to investigate the association between socioeconomic variables, urbanicity, and AC prevalence. The results align with previous studies where Black households had lower rates of central AC ownership (O’Neill et al., 2005). The present study confirmed lower magnitude AC access disparities by race, income, and geographic location. There is limited research investigating AC ownership in rural areas and thus a limited understanding of the factors that contribute to rural residents’ access to AC. However, rural residents are more likely to be lower income, have a lower level of education, and are more likely to be an immigrant. There is some evidence that racial areas have a higher proportion of lower-income, lower-education, and immigrant populations; which may explain lower AC prevalence in rural areas (Bollman & Reimer, 2009; Pew Research Center, 2018).

Moreover, areas with historically Black or African American populations are positively associated with the proportion of not having AC. These results reveal that redlining still affects residential segregation, the disproportional development of contemporary society, and disparities in health and well-being (Mehdipanah et al., 2023). Thus, we believe that redlining contributes to a lack of AC ownership and increased risk of heat exposure.

This study confirms earlier findings that some socioeconomic variables, such as percent renter-occupied households, show a significant association with the lack of AC prevalence (Bock et al., 2021; Klein Rosenthal et al., 2014; Williams et al., 2019). This study also considered property variables that may be associated with AC prevalence. The mean of the built year of property showed a significant inverse relationship with the percentage of households without AC. This result aligns with previous research on AC estimation models with the American Housing Survey data.

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**Table 3. Beta coefficient with 95% confidence intervals from Spatial Durbin Model.**

| Variables                        | Direct (95% confidence interval) | Indirect (95% confidence interval) | Total (95% confidence interval) |
|----------------------------------|-----------------------------------|------------------------------------|-------------------------------|
| Built Year                       | −0.01*** (−0.02,−0.01)            | 0 (0.0)                            | −0.01*** (−0.02,−0.01)        |
| Total area of property (Square ft)| −0.06*** (−0.1,−0.02)             | 0 (−0.02,0.01)                     | −0.06*** (−0.1,−0.03)        |
| Urbanicity (Metro UC)            | 0.15*** (0.10,0.19)               | 0.04*** (0.00,0.07)                | 0.18*** (0.12,0.25)          |
| Urbanicity (Rural)               | 0.3 *** (0.25,0.35)               | 0.09 (0.04,0.14)                   | 0.39*** (0.31,0.47)          |
| % Over 65-year-old               | 0 (0.0)                           | 0 (0.0)                            | 0 (−0.01,0.01)               |
| % Black African                  | 0.01 *** (0.00,0.01)              | 0.00 *** (0.00,0.01)               | 0.01 *** (0.00,0.01)         |
| % Renter Occupied                | 0 (−0.01,0.00)                    | 0 (−0.01,0.00)                     | 0 (−0.01,0.00)               |
| Median household income in the past 12 months (in 2019 inflation-adjusted dollars) | 0 (−0.01,0.00) | 0 (−0.01,0.00) | 0 (−0.01,0.00) |
| % Hispanic or Latino             | 0 (0.0)                           | 0 (0.0)                            | 0 (−0.01,0.00)               |
| Median property value (dollars)  | 0 (0.0)                           | 0 (0.0)                            | 0 (−0.01,0.00)               |
| Number of room per resident      | −0.01 *** (−0.01,−0.00)           | 0 (−0.01,0.00)                     | −0.01*** (−0.02,−0.00)       |
| % Historical Black African       | 0.01 *** (0.00,0.01)              | 0 (0.0)                            | 0.01 *** (0.00,0.01)         |
| % Complete plumbing households   | −0.01 *** (−0.01,−0.00)           | 0 (0.0)                            | −0.01 (−0.01,0.00)           |

*Significant at 90% intervals.  
**Significant at 95% intervals.  
***Significant at 99% intervals.
Metro Clusters had the strongest positive relationship with the percentage of properties without AC. Rural Clusters showed the second strongest relationship with the percentage of properties without AC. We believe that this association reflects Florida’s urban development history. Core urban areas tend to have older apartments and houses (Schwartz, 2006) where disadvantaged populations live (Wilson et al., 2010). The Federal Housing Administration refused to pay for AC renovations in inner urban houses, areas with low home values, and areas with a high ratio of foreign-born residents (Nardone et al., 2021; Warner & Tilly, 1995). ‘White flight,’ or the migration of Anglo Americans from urban areas to the suburbs after the passage of the Fair Housing Act of 1968, contributed to lower capital investment and urban housing quality.

To minimize overall health risks associated with heat, policies, and programs such as the Housing Energy Assistance Program and Low-Income Home Energy Assistance Program (LIHEAP) should target neighborhoods with low AC prevalence and/or lower socioeconomic position status (Fraser et al., 2017). Moreover, jurisdictions should consider supporting the installation of central AC since other types of AC, such as a wall, window, and portable AC, are not as effective at mitigating heat-related symptoms and illness (Quinn et al., 2017; Waugh et al., 2021). We will need to consider providing subsidies for installing central AC, electricity bills, or improving housing conditions. Increasing green space and designating cooling centers in neighborhoods with less AC prevalence could be other options.

This study has illustrated several strengths of utilizing real estate data to analyze disparities of AC ownership in Florida. However, there are a few limitations that should be addressed. Cluster analysis is constrained by the data available data, much of which was missing. The number of properties indicating AC type as ‘No’ is relatively less than those indicating AC type as ‘Central, Window, Wall or Others.’ Also, some parts of Florida, such as Leon County, Miami-Dade County, and Union County, have a high proportion of properties without AC information. There may be spatial disparities of AC ownership in these areas, but it was not possible to detect them due to limited data availability. The results should be interpreted with caution. For example, Appendix Figures 1 and 2 illustrate variables data distribution according to urbanity and cluster types. Any significant spatial clusters found in rural areas for yes AC and Metro_UA, and Metro_UC seem to have similar observations (Appendix Figure 1-A). Fewer observations were used in rural areas without AC clusters (Figure 2-A). This indicates that the rural clusters might have been an artifact of the data.

There are limitations to estimating housing characteristics from historical property records. This study aggregated all types of AC due to non-standardized AC reporting practices. For example, some jurisdictions only indicated AC ownership as ‘yes’ instead of reporting a specific type of AC. Moreover, how AC information is coded is unclear. For example, no AC can be recorded as unavailable or not having any AC. However, a few studies showed that wall, window, or portable unit AC is not as effective as central AC (Cardoza et al., 2020; Quinn et al., 2017; Waugh et al., 2021). Additionally, this database did not report the exact dates when housing information was updated and may miss recent improvements that are not reflected in the dataset. Nationwide AC ownership information should be gathered in the future, and it will benefit researchers and governmental decision-makers. In addition, we recognize the limitation of the spatial scale of socioeconomic variables. We applied aggregated sociodemographic information at the census tract level.

To address this study’s limitations, future research should collect fine-scale data that will produce more actionable results for urban planners, housing advocates, and public health officials (Reid et al., 2009). Utilizing AC has been shown to significantly reduce heat-related mortality rates and illnesses, which are important and growing public health concerns under a changing climate (Barreca et al., 2016; Ito et al., 2018; O’Neill et al., 2005). Moreover, providing guidelines for adequate AC utilization and energy subsidies will be helpful for alleviating the financial burdens of economically disadvantaged groups (Ito et al., 2018; Loughnan et al., 2015).

5. Conclusions

This study identified neighborhoods and vulnerable groups across Florida lacking access to residential cooling systems. This study also contributed to gaps in existing research on AC prevalence by applying more recent real estate data on AC ownership at the census tract scale, and utilizing spatial regression analysis to understand disparities across socioeconomic variables. We found variability in AC prevalence by urbanicity and sociodemographic characteristics, particularly race, property size, and year of construction. Based on our findings, we discuss the potential benefits of gathering nationwide fine-scale AC ownership data and recommend heat prevention measures for vulnerable groups that include improving access to services such as LIHEAP, distributing AC units, and installing cooling centers in areas with low AC prevalence.

Software

Software: Arc GIS Pro. Projected coordinate system: World Geodetic System 1984 (WGS84).
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Disclosure statement
The authors declare that they have no known competing financial interests or personal relationships that could reasonably be perceived to have influenced the work reported in this paper.

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Data Availability Statement
The archive data are from property data from Estated (Estated, 2021). Socioeconomic variables are available from the American Community Survey of the United States Census Bureau (United States Census Bureau, 2011, 2019). The NHHGIS provides historical demographic information (IPUMS NHGIS, 1970). Urban and rural codes were collected from the USDA (United States Department of Agriculture (USDA), 2013).

Authorship confirmation/contribution statement
YJ and CU conceived the manuscript together and participated in planning the writing, workflow, and timeline. YJ conducted the analysis and wrote the final manuscript. SW, EP, and TH contributed to the discussion and iteratively incorporated it into the third and fourth drafts. All authors read and approved the final manuscript.

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Appendix

Figure 1 and Figure 2 show the comparison of the variables’ distribution according to the cluster types. Figure 1 represents the variables’ distribution of any kind of AC, and Figure 2 illustrates the distribution of variables without AC.

Figure A1. Comparison of variables with any AC according to urbanity and spatial clusters.
Figure A2. Comparison of variables without AC according to urbanity and spatial clusters.