ABSTRACT

RANDALL, JOSHUA N. Scales of Energy Justice: Understanding Energy Poverty Through Multi-scale Spatial Analysis. (Under the direction of Drs. Jelena Vukomanovic & Bethany Cutts).

Nearly 1.4 million people in North Carolina and over 25 million households in the US experience energy poverty - they are unable to both secure energy and acquire other basic human needs simultaneously. Spatial analysis has the potential to improve energy poverty policy implementation by identifying disproportionate energy burdens due to social characteristics, the built environment, and climate variability. While aggregating spatial data is an effective way to protect household privacy, it also has the potential to hide experiences of energy poverty. A key challenge for energy poverty policy implementation is how to use aggregated data to identify unique signatures of regional, community, and household-level energy poverty that are not sufficiently addressed through one-size-fits-all approaches. In this dissertation, I analyze energy poverty using geographic scale and location as lenses for understanding policy equity. My first paper addresses the current state of spatial energy poverty analysis through a semi-systematic literature review, discerning current trends and potential areas of data bias present in the field. My second paper addresses the identification of energy poverty vulnerabilities in North Carolina through principal components analysis (PCA) at multiple scales, finding some energy poverty experiences can be identified regardless of scale, while others are scale-specific. My third paper uses an energy use intensity (EUI) estimation method coupled with a multiscale weighted regression (MGWR) to explore the spatial relationship of socioeconomic characteristics with EUI in the Eastern US. The results indicate characteristics vary widely in the geographic scale of their relationship to EUI. Collectively, the results of this dissertation point to a need for local and national policy to address scale as an equity component of energy policy interventions. Further,

this dissertation offers a suite of methods for scholars and practitioners who seek to use spatial analysis as a tool for resource equity.

Scales of Energy justice: Understanding Energy Poverty Through Multi-scale Spatial Analysis

by
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DEDICATION

This dissertation is dedicated in two parts. First, to my family for their immeasurable support, both monetarily and emotionally. Graduate school takes its toll, and my family was there every step of the way. This is as much their dissertation as it is mine. Second, I would like to dedicate this dissertation to everyone past, present, and future who are affected every day in the US and around the world by the inability to have full autonomy over their own bodies. This should not be the world we live in, and we must do better.

BIOGRAPHY

Joshua was born March 1, 1990 in Cheyenne, Wyoming to Robb and Amy Randall. As a military child, he moved many times and saw many parts of the world while young. He moved to Vail, Arizona and attended Cienega High School and graduated in 2008. He attended Arizona State University as an honors student in Barrett Honors College. Here he found his love of geography and sustainability and graduated with a BS in both Geography and Sustainability. He then attended Rutgers University for an MS in Geography, graduating in 2014. He worked at the University of Iowa in Iowa City for the Iowa Flood Center for a year and a half, and then moved to the New Mexico Water Resources Research Institute in Las Cruces, NM working for another year and a half. He moved to Raleigh in 2017 to begin a PhD in Parks, Recreation, and Tourism Management under the direction of Bethany Cutts and Jelena Vukomanovic.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

Four billion people around the world experience energy poverty - they are unable to both secure energy and acquire other basic human needs (Tomei & Gent, 2015). Many community agencies, policy programs, and research studies have tried identifying energy poverty in communities using geospatial technologies and data. These efforts are often implemented to identify vulnerable populations and help those who need them (Castán Broto & Baker, 2018; Lacey-Barnacle et al., 2020). Energy poverty is recognized as a phenomenon that is a result of many intertwined socio-technical systems (Baker & Beer, 2007; Day & Walker, 2013; Harrison & Popke, 2011; Jenkins et al., 2014). While increasing the capability to understand spatial patterns of energy poverty metrics, geospatial studies of energy poverty are unable to fully capture systematic connections and understand the justice implications of energy poverty or capture scalar and locational differences in energy poverty experiences (Bouzarovski & Simcock, 2017; Herrero, 2017). This leads to a consistent lack of clarity within spatial energy poverty research and policy on the proper metrics to use when targeting energy poverty.

While energy poverty is beginning to be analyzed as a spatial phenomenon, the implications of spatial analysis as a justice issue in identifying energy poverty are less researched. The many parts of energy poverty policy are often explicitly linked to disparate spatial boundaries (Bouzarovski & Simcock, 2017; Bridge, 2018; Horner et al., 2011; Sareen et al., 2020). However, energy utilities are not bounded by political boundaries but by their infrastructure footprint. Therefore, when targeting energy poverty data aggregated to the county will provide a different (but perhaps not incorrect) view of an area than will data aggregated to a utility service area. The decisions to use either of these scales may be appropriate, but the outcomes of those decisions must be analyzed critically to understand the capacity to which they capture the appropriate signatures of energy poverty. However, energy poverty is felt at a household level (Walker et al., 2014) and the lack of attentiveness to this variation between households, particularly in the form of aggregated spatial scales of analysis can often "hide" experiences of energy poverty (Meyer et al., 2018). Further, when these experiences become a pattern, they are issues of justice, where both outcomes and solutions are not evenly distributed across space. Because policy is often written for attribution to geographic scales larger than a household it is important to recognize how data aggregation and geographic scale selection alter how energy poverty is detected. While the recognition of this issue is noted in previous research (Sareen et al., 2020; Warren, 2014), there are very few approaches explicitly linking geography as a form of energy poverty injustice. Recognizing the implications of geography in energy poverty work is vital for reformulating energy poverty policy to address unforeseen justice issues. The main objective of this dissertation is to provide a base for linking explicit spatial analysis to identifying the social justice implications of energy poverty, or *energy justice*. This is achieved through three goals that form the basis of the dissertation.

Chapter 2, a semi-systematic literature review titled "Data trends of spatial energy poverty research: A Literature Review, aims to survey the current field of energy poverty to both understand the landscape and recommend areas to push the field. Because the energy poverty field and the spatial analysis methods are relatively new, there is not a comprehensive examination of their intersection, nor a recognition of the possible biases inherent in the research in the field. In this paper, I collect seven variables from 43 papers to understand how data source, energy poverty's operationalization, and study location can affect current understandings of energy poverty. A set of recommendations are provided to evaluate the implications of geography and bias in spatial energy poverty research.

Chapter 3, Scale Agnostic and Scale Specific Indicators of Vulnerability to Energy Poverty, aims to highlight how a single geographic scale spatial analysis may alter the results of identification of energy poverty. Scale is a contentious yet inevitable aspect of spatial analysis, however not recognizing the implications of different scales of reference in spatial analysis may hide from energy poverty that needs addressing. In this paper I first identify what I term *energy poverty signatures* or groupings of energy poverty vulnerability characteristics, using a Principal Components Analysis at a census tract level. Once identified I repeat this process for two other geographic scales and compare the differences in energy poverty signature identification. Then I use a Geographically Weighted Principal Components Analysis to identify spatially specific changes of energy poverty signatures between scales. This paper is intended to inform policy on what is missed and how to improve energy poverty identification that is just in its outcomes.

Chapter 4, Multi-Scale Spatial Analysis of Estimated Energy Use Intensity and Socioeconomic Indicators of Energy Poverty, uses modeled energy use data to identify the spatial scale of relationships between energy poverty characteristics and energy use. Energy use is difficult to access for large areas due to the availability of data. Simultaneously, social characteristics of energy poverty (i.e., race, income, housing) are occurring and intertwining at different scales. Understanding the scale of these processes and how they interact, and the scale at which they interact is vital to match effective policy to address issues. To address this, I first create an estimated energy use model by county. Using this model, I used a multiscale geographically weighted regression to identify the multiple scales of each characteristic to understand the spatial and scalar patterns of influences. These results provide a starting point in how a flexible energy poverty policy can address different aspects of energy poverty simultaneously.

These papers can address the spatial aspects of energy justice, which I term in Chapter 2 as *spatial energy justice.* Chapter 2 identifies the current state of the academic field and identifies current trends of research and is useful to academics and practitioners to understand what, how, and where energy poverty is over or under-researched. Chapter 3 provides a useful methodology for the identification of multiple scales of energy poverty signatures. This is useful to create a more targeted and just policy and answer the question, who are we missing? Chapter 4 uses an energy use model to tie social characteristics to top energy use, to understand the scale at which these social processes interact. These methods are useful for anyone attempting to understand how to simultaneously address different aspects of energy poverty policy. Taken together, these methods provide a way to tie spatial energy justice to policy. Not only to identify areas of concern but to provide novel methods to address energy poverty in just ways.

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CHAPTER 2: DATA TRENDS OF SPATIAL ENERGY POVERTY RESEARCH: A LITERATURE REVIEW

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Abstract

Energy poverty is a relatively nascent field, with an academic focus occurring only in the last 30 years. As the field has grown, an influx of GIS and geospatial analyses are being used to understand the spatial components of the energy system as it pertains to energy poverty. This growth results in a need to review the role of geospatial tools in energy poverty and understand possible areas of bias to steer the development of geospatial applications to energy poverty dilemmas. To accomplish this, we performed a semi-systematic review to identify the body of spatial energy poverty research. Identifying energy poverty research with an explicit spatial component, six variables were extracted after a review of each study: spatial variables, spatial data source, spatial variable unit, energy poverty pathways, location, and geospatial analysis methodology. A review of the collected variables shows an increase in research in the last 5 years. Further, most research is collected through government sources, and nearly all research is performed in Europe and North America. The results indicate a need for the field to diversify in all aspects to ensure the efficacy of results for both the field and policy interventions. Other recommendations include a push to increase data sharing and multi-scale, multi-source analysis. This review provides a current benchmark of the field for researchers and practitioners interested in spatial energy poverty.

Keywords: GIS; Energy Poverty; Literature Review; Spatial Justice; Energy Justice

Introduction

Energy poverty is the “inability to attain a socially and materially necessitated level of domestic energy services” (Bouzarovski & Petrova, 2015, p. 31). Energy poverty is shown to interact with a variety of energy social and structural characteristics of a household (Hernández, 2015; Martín-Consuegra et al., 2020). Further, energy systems and thus energy poverty are recognized as geographically driven systems and outcomes, meaning the overlapping and intertwining parts of energy poverty create new and intricate outcomes that are not the sole cause of one part of the system (Bouzarovski & Simcock, 2017; Robinson et al., 2017). The effects of the energy system leading to energy poverty are inherently complex. As the field of energy poverty advances, there is a periodic need to evaluate the data sources and analytical tools used to identify experiences of energy poverty and influence policy change. We used a semi-systematic review method to summarize and evaluate the emerging role of geospatial tools in energy poverty studies.

This review was evaluated through the lens of spatial energy justice. Here, we term spatial energy justice as the conceptualization of energy justice and spatial justice as coexisting justice frameworks. Energy justice is concerned with understanding the equity of outcomes of the energy system, specifically focusing on distributive justice, or where benefits and burdens are, procedural, or justice within political structures, and recognition, or highlighting all populations and experiences (Bouzarovski & Simcock, 2017; Hernández, 2015; Jenkins et al., 2014). Spatial justice, conceptualized by Soja (2010) and based on the works of Young (1990) and Harvey (1973, 1996), is focused on social justice and space, and in particular how decisions and processes drive injustice as a function of geography. Combined, spatial energy justice highlights the unequal processes and outcomes of the energy system through geography.

Outcomes of research are major factors in highlighting spatial energy justice, such as the distribution of energy poverty or political interventions based on location. However, a spatial energy justice framing refocuses how geospatial analytics and geographic information systems (GIS) can best support energy poverty policy implementation as part of the knowledge creation process. There are potential areas of bias in spatial energy poverty research that may also include spatial energy justice concerns. The frame highlights three potential areas of bias in spatial analysis of energy poverty - data source, energy poverty's operationalization, and study location. From these overarching frames, six variables were reviewed in each paper to better help highlight the potential spatial justice biases. These variables are the original spatial variable, energy poverty pathways, spatial data sources, spatial variable unit, location of study, and geospatial methodology.

Energy poverty is inherently spatial (Bouzarovski & Simcock, 2017; Herrero, 2017). There are well-documented relationships between spatial variables that capture neighborhood sociodemographic characteristics and the prevalence of energy poverty (Herrero, 2017). Spatial variables are defined in this work as a variable that is or was created with a locational component, such as linking demographics to census tracts. Thus, GIS can be an effective tool to document the distribution and degree of disparity in conditions of energy poverty (Castán Broto & Baker, 2018). However, many of the correlations between end-users of energy and their neighborhood sociodemographics are generalizable to other forms of poverty, social, and environmental injustice (Graff et al., 2019; Hernández, 2015). Thus, while these indicators of social vulnerability to energy poverty can be a useful tool for identifying some households that might benefit from financial services that offset energy costs(Murray & Mills, 2014) or policy interventions (Walker et al., 2013), other geospatial approaches can better analyze the impacts of spatial processes generating energy poverty.

Just energy policy must be attuned to unique energy poverty pathways. Energy poverty pathways are defined as the broad causes of a particular energy poverty experience. Fuel production and utility distribution, for example, generate energy poverty at much larger extents than the insulation level of a building. Yet both may simultaneously contribute to the lived experience of energy poverty (Bouzarovski & Simcock, 2017). Geospatial applications may aid efforts to identify and disrupt systems that generate energy poverty (Bouzarovski & Simcock, 2017; Castán Broto & Baker, 2018). Bouzarovski and Petrova (2015) identify 6 distinct energy poverty pathways (or what they term typologies). These are access, affordability, flexibility, energy efficiency, needs, and practices. These are intended to capture the wide range of energy poverty experiences that are both broad enough for classification but specific enough for intervention; each energy poverty pathway has a unique set of causes. However, the extent to which spatial variables are being used to identify distinct systems that contribute to experiences of energy poverty is not known. Developing indicators of pathways that contribute to systemic inequities have the potential to shift policy attention to the origin of harm instead of the locations of impact (Soja, 2010).

Despite the potential for spatial methods to elucidate energy poverty types, geospatial studies can also generate new weaknesses concerning spatial injustices (Bouzarovski & Simcock, 2017; Castán Broto & Baker, 2018). First, Spatial data sources have the potential to introduce research bias. Spatial data sources in this review are defined as the original entity collecting the data. In spatial analysis, the use of secondary data is common practice (St Martin & Pavlovskaya, 2010). Practically, it can be financially and temporally prohibitive (or downright unethical) to collect original data for every use scenario. Understanding the trustworthiness and original intent of data sources is important to robust policy analysis (D’Ignazio & F. Klein, 2020). Spatial datasets are often collected and disseminated by government agencies, nonprofits, private companies, and academia (St Martin & Pavlovskaya, 2010). Government sources include any state-owned government agency of a particular country that collected and distributed the data, specifically of which federal funding was used. Non-profit sources are sources that are obtained through a designated non-profit entity that is non-government or academic. An academic source is an individual or a group affiliated with an academic institution that created the data, which may include items such as surveys as part of the project.

A second complication with geospatial analysis is establishing the influence of the spatial variable unit used for data collection. The spatial variable unit is defined in this case as the geographic scale of the variable in question being used as the variable, such as a census tract or county. Analysis that uses data aggregated to a political boundary or a consistent areal unit has the potential to contribute to a “confusion” of scales, where aggregating data misrepresents heterogeneous spatial patterns across a landscape (Nelson & Brewer, 2017). The implications of confusion across scale is that policy addressing energy poverty could be misapplied and ineffective at improving energy poverty experiences. A lack of implementation reinforces previous inequities, especially for people or locations already socially disadvantaged (Bickerstaff & Agyeman, 2009; Fisher et al., 2006). Scale is a longstanding concern in geography where representations of the problem are apparent through the Modifiable Areal Unit Problem (MAUP) (A. Fotheringham & Rogerson, 2009; Nelson & Brewer, 2017). MAUP addresses how the selection of boundaries and scale alter the outcomes of the study. Therefore the use of data at different scales implies that either it is accepted that the areas of study are known to be homogenous, or that it does not matter if they are homogenous to the study (Wei et al., 2016). In either case, the use of metrics at an aggregated scale for energy poverty has the potential to ignore differences within the spatial unit selected (Bouzarovski & Simcock, 2017). Although the spatial unit of data is often determined by decisions made to retain the privacy of individuals, the overreliance on data aggregated to default scales potentially obscures critical relations between energy poverty drivers. For example, census-tract level analytics may suggest low levels of energy poverty and de-prioritize a region for assistance while individual households struggle to heat (Walker, Liddell, et al., 2014). Therefore, the selection of scalar analysis within spatial energy poverty studies may alter the detection of energy poverty, or not fully represent patterns that may be occurring.

Third, study location selection is often driven by opportunities for policy change and, if not examined critically, can lead to analytic approaches that derive their validity from contextual factors being misapplied to other regions (Martin et al., 2012).

Fourth, the choice of geospatial methodology - or the statistical research method selected by the researcher, is less straightforward on bias assumptions but requires categorization to survey the field. Spatial methodology falls into two categories, with specific assumptions for either case. The first is the assumption of the outcome of spatial energy poverty and associated spatial variables as spatial. This is most associated with the creation of non-spatial indexes and mapping them to some designator, such as a vulnerability index based on demographic variables. The second is the assumption of energy poverty and associated processes as explicitly spatial processes. This often occurs through analysis such as geographically weighted regressions and other analyses that use space and distance as explicit drivers within the model (S. Fotheringham et al., 1998). While the outcomes can be interpreted in several ways, it is important to recognize that the assumptions of the models and studies and the questions they are asking must align.

This literature review provides a benchmark of current spatial energy poverty research. Results from this study were discussed as possible areas of concern for potential bias and equity concerns, and recommendations were made to help fill current gaps in research.

Methods

To evaluate how spatial energy poverty studies operationalize geospatial data to evaluate energy poverty, we completed a semi-systematic review of the literature on spatial energy poverty. The rationale for using a semi-structured approach was to capture both the diversity of peer-reviewed empirical work related to energy poverty and the most influential policy (Semananda et al., 2018; Welsh, 2018). While peer-reviewed literature can be reliably captured by databases of indexing services, gray literature is less universally indexed. The study is constrained to English-language publications indexed from the years 2000 to 2020. The period corresponds with the earliest GIS applications in spatial energy poverty work (Baker et al., 2003). The potential limitations of this inclusion frame are discussed later in the manuscript.

Data Collection

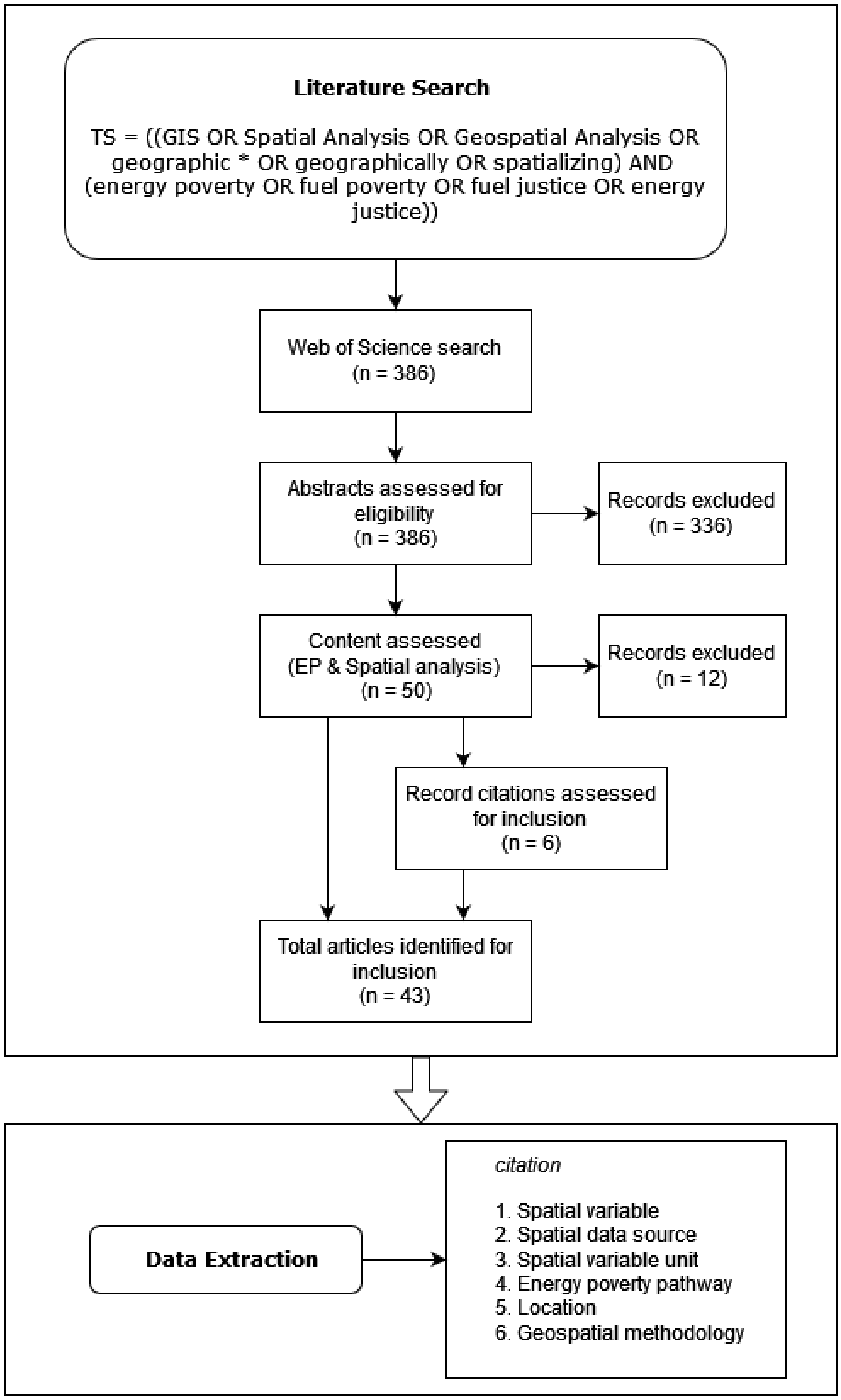
To identify applications of geospatial analytics to energy poverty studies, we developed a semi-structured search protocol as outlined by Hunter and Luck (2015). Figure 2.1 outlines the review procedures. The scope of the literature review includes spatial analysis of energy poverty. The research question and a set of 9 influential spatial energy papers helped establish search criteria for a systematic literature review. First, nine influential spatial energy poverty research papers, listed in Table 2.11 in the appendix, were selected based on distinct use of spatial analysis to study energy/fuel poverty. We created selected rules to maximize the diversity of author identities (i.e. gender and geographic location of institution and study area) and established rules to limit the influence of individual authors (no author represented more than twice). These key papers helped to develop a keyword search before a structured literature review.

We completed the structured portion of the literature review using Web of Science (WoS) online database of scientific research literature. WoS is commonly used in academic literature reviews and results are reproducible (Singh et al., 2021). We removed articles from the review if they (a) were not explicitly related to energy or fuel poverty, or (b) the methods of the full text do not include geospatial data and methodologies.

Next, we analyzed the cited references from each of the works included in the structured review to inform. This approach uses a snowball method of citation inclusion to expand the literature pool by identifying literature cited more than once and not captured by WoS. This enabled us to capture other influential work that may not be indexed by academic search engines (Spruijt et al., 2014). We included only one generation of snowball citations.

Figure 2.1

Workflow of semi-systematic literature review, indicating the number of papers remaining after each step



Data analysis

To extract data from each paper, we reviewed the full text of each manuscript by hand. Along with a full citation, we coded the following details from each paper: (1) spatial variable (2) spatial data source (3) spatial variable unit (4) energy poverty pathways, (5) location, and (6) geographic methodology. Table 2.1 describes the data collected as part of the review. These coded elements roughly correspond to key opportunities to align data collection, operationalization, and analysis phases of geospatial research with spatial justice. **Spatial variables** are any variables represented with a geographic location used in any of the spatial studies in the search. Spatial variables themselves were not categorized but used to index the rest of the variables. These are reported as **individual variables** and may have more than one per publication. **Spatial data sources** are categorized into four main sources, Government, non-profit, privately owned, and academic/researcher produced. These were categorized based on an initial review of the data by the authors. Spatial data sources are reported by **individual variables**. **Spatial variable units** are categorized into six units: Continental, country, county/regional, city/town, census division/voting division, and household or below. The spatial variable units were categorized by the authors based on a review of the unique spatial units for each **individual variable. Energy poverty pathways** are originally based on (Bouzarovski & Petrova, 2015) and were adjusted to fit the scope of this review, as they do not fully capture the range of analyses in spatial energy poverty. Pathways were categorized as the general cause of energy poverty that was the frame of the analysis. The pathways are access and stability, or energy poverty due to the inability to access stable energy sources. Affordability, or energy poverty due to the inability to afford energy. Socio-economic, which is energy poverty experienced due to socio-economic status outside of income; Energy-efficiency, or energy poverty experiences occurring through a lack of built environment efficiency; and Policy, or energy poverty through lack of or poor political interventions. This is reported by **individual study**, however, each study may have multiple designations. For example, Mashhoodi et al. (2019) focused research on homogenous indicator variables was classified with a socioeconomic, affordability, and efficiency pathway as all were used to frame the research. **Location** is categorized by individual locations of the study and then categorized by continent of the study location for clarity and ease of analysis. These are reported by **individual study**. Although some studies did have multiple locations of analysis, none were cross-continent. **Geospatial methodology** is categorized into unique spatial analysis methods as reported by each study. These are reported by **individual study** and may have multiple per study.

Following data extraction, we examined the distribution of literature across categories within each theme and through cross-tab analysis. The purpose is to explore patterns of interaction between variables and to highlight areas of further analysis or potential bias.

Table 2.1

Literature review collected variables, classifications, and descriptions

Variable	Unit of reporting	Classification	Description or Examples
Spatial Variables	Variable	Unique	*Median income; heating degree days*
Spatial Data Sources	Variable	Government	*US Census*
		Non-profit	*Salvation Army; Natural Earth*
		Private	*utility data*
		Academic/Research	*survey data*
		unknown	-
Spatial Variable Unit	Variable	Continetal	*Africa*
		Country	*England*
		County/Regional	*Subsaharan Africa; US Counties*
		Town or City	*Barcelona, Spain*
		Census or Voting Division	*UK Census Lower Layer Super Output Areas (LSOA); US Census Tracts*
		Household or below	*30m raster; Household*
Energy poverty pathway	Study	Access and Stability	energy poverty through inability to access stable energy sources
		Affordability	energy poverty through inability to afford energy
		Socio-economic	energy poverty experiences due to socio-economic status
		Energy-efficiency	energy poverty through a lack of structural efficiency
		Policy	energy poverty through lack of proper political intervention
Location	Study	Unique	*Barcelona, Spain; Kansas City, MO*
Geospatial methodology	Study	Unique	*Moran's I; GWR*

Results

The semi-structured literature search protocol identified 43 papers in WoS after completing topic filtering. Four more were identified through snowball citation search (Figure 2.1; full citations in appendix Table 2.12). Publication dates ranged from 2008 to 2020.

Table 2.2

Number of publications by year

Year	# of publications
2008	2
2009	0
2010	0
2011	1
2012	0
2013	2
2014	3
2015	1
2016	4
2017	7
2018	4
2019	11
2020	13

In total, we identified 360 unique spatial variables through this review. On average, papers used eight distinct variables (min 1, max 31). Seventy-five percent (271) of spatial variables were collected from government data sets, which include government agency collection and reporting. 5% were acquired from nonprofits, 5.6% from private companies, 2.5% from academic sources, and 9% were created by the researcher (Table 2.3). Government sources include any state-owned government agency of a particular country that collected and distributed the data. These most often came in the form of census data, including the US and UK Census. It also includes data produced by government labs such as the National Aeronautics and Space Administration (NASA). A count of unique sources resulted in a majority of spatial variable units occurring at census level geography (24). Households were the next most common (Table 2.4). Analysis of energy poverty pathways reveals 11 papers focused on access, 23 on affordability, 28 on socio-economic, 30 on energy efficiency, and 12 on policy (Table 2.5). Papers most commonly focused on locations within Europe (61%), North America accounted for

17% of studies. The remainder were split between Asia, South America, and Africa (Table 6). Finally, the review yielded 22 unique geospatial methodologies. The most common method was a spatial presentation of indexes and other calculations (45%), geographically weighted regression (GWR) was next-most common (9%) along with the spatial clustering model known as Moran's I (9%).

Table 2.3

Spatial variable sources totals

Spatial Variable Source	#	%
government	271	75.3%
researcher	34	9.4%
private	20	5.6%
non-profit	18	5.0%
academic	9	2.5%
unknown	8	2.2%
Total	360	-

Table 2.4

Spatial variable unit totals

Spatial Variable Unit Scale	# of Unique Variables
Continental	1
Country	3
County/Regional	4
City/Town	5
Census Division/Voting Division	24
Household and below	10
Total	12

Table 2.5

Energy poverty pathways totals

Energy poverty pathways	#	%
Energy efficiency	30	28.8%
Socio-Economic	28	26.9%
Affordability	23	22.1%
Policy	12	11.5%
Access & Stability	11	10.6%
Total	104	100%

Table 2.6

Location of studies

Location	# of publications	%
	Europe	
England	8	
Ireland	5	
Northern Ireland	3	
Portugal	3	
The Netherlands	3	
UK	3	
Madrid	2	
Bicester, UK	1	
Italy	1	
London	1	
Stirling; UK	1	
Sweden	1	
Total	32	61.5%
	North America	
Chicago, IL, US	1	
Detroit, MI, US	1	
Kansas City, MO, US	1	
New York City	1	
Phoenix, AZ, US	1	
Riverside, CA, US	1	
San Bernadino, CA, US	1	
Texas	1	
Washington D.C., US	1	
Total	9	17.3%
	Africa	
Africa	3	
Nigeria	1	
Sub-Saharan Africa	1	
Total	5	9.6%
	Asia	
India	2	
Amaravati, India	1	
China	1	
Nepal	1	
Total	4	7.7%
	South America	
Brazil	1	
Chile	1	
Total	2	3.8%
Total Locations	52	-

Table 2.7

Geospatial methodologies

Geospatial Methodology	Number	%
mapped non-spatial analysis output	17	25.0%
mapped index	14	20.6%
GWR	6	8.8%
Moran's I Analysis	6	8.8%
LISA clustering analysis	3	4.4%
comparison mapping	2	2.9%
emissions modeling (DECoRuM)	2	2.9%
k-means cluster analysis	2	2.9%
SGWR	2	2.9%
spatial error modeling	2	2.9%
spatial lag model	2	2.9%
GWPCA	1	1.5%
linear mixed modeling	1	1.5%
location summary	1	1.5%
location-allocation analysis	1	1.5%
peer-to-peer machine learning	1	1.5%
sale deliminator	1	1.5%
siting index	1	1.5%
suitability model	1	1.5%
travel time optimization	1	1.5%
UHI modeling	1	1.5%
Total	68	100%

Three crosstab analyses were performed after counts for each variable were analyzed, between the spatial variable unit and energy poverty pathway, spatial variable unit and energy poverty pathway, and spatial variable unit and location. These crosstabs were included as they provide patterns of coincidence between the three major forms of bias, data source, energy poverty’s operationalization, and study location. Number totals may not align with one another or previous work due to the extrapolation of totals between a variable unit and a publication. For example, each variable was assigned the publication energy poverty pathway to provide a crosstab.

Table 2.8

Energy poverty pathway and spatial variable unit crosstab totals

Spatial Variable Unit	Access & Stability	Affordability	Socio-Economic	Energy efficiency	Policy	Total
Continental	4	0	0	4	0	8
Country	2	0	0	6	2	10
County/Regional	5	0	29	0	29	63
City/Town	27	18	15	14	3	77
Census Division/Voting Division	48	189	191	187	56	671
Household and below	16	24	47	37	19	143
Unknown	4	5	2	10	2	23
Total	106	236	284	258	111	995

Table 2.9

Spatial variable source and spatial variable unit crosstab totals

Spatial Variable Unit	Government	Private	Researcher	Academic	Non-Profit	Unknown	Total
Census Division/Voting Division	185	14	14	5	3		221
City/Town	13	1	11		14		39
Country	7		1		1		9
County/Regional	37	4	1				42
Household and below	40	5	13	3	4		65
Multi-county/Continental			1	1	2		4
Unknown			5			7	12
Total	282	24	46	9	24	7	392

Table 2.10

Spatial variable unit and location crosstab totals

Location	Census Division/ Voting Division	City/ Town	Country	County/ Regional	Household and below	Multi-county/ Continental	Unknown	Total
Asia	6	17	2		16			41
Africa		10		5		4	2	21
Europe	154	1	6	29	32		10	232
North America	58				13		2	73
South America	3	3						6
Total	221	31	8	34	61	4	14	373

Discussion

This review provides the groundwork to situate how knowledge is being created in the nascent field of spatial energy poverty, with particular interest paid to three potential areas of bias in spatial energy poverty analysis - data source, energy poverty's operationalization, and study location. The most common pattern was the prevalence of spatial analysis performed in Europe and North America and a strong reliance on data from government sources. This coincided with reliance on census-designated areas as the spatial unit of both analysis and reporting.

Results of this semi-structured literature review also indicate that there is a small but growing number of explicitly spatial analyses of energy poverty. Although energy poverty as a concept is relatively well known and identified globally (Bouzarovski & Petrova, 2015; Heffron et al., 2015; World Energy Council, 2016), our findings reinforce the idea that spatial analysis of energy poverty is still maturing. Guiding the maturation of spatial data applications to energy poverty policy will ensure better alignment between spatial analytics and just policy outcomes. In the discussion below, we interpret observed patterns and trends in the light of opportunities to overcome data biases as the field matures.

To date, research on **energy poverty pathways** mostly focuses on affordability, socio-economics, and energy efficiency. This is expected as these three pathways are the most common and traditional frameworks of energy poverty (Bednar & Reames, 2020) and are used to quickly survey energy poverty. The two remaining pathways, accessibility and policy, are lower. This may be in part due to the lack of spatial data concerning the flexibility of energy use sources, and in areas where this is available, many households do not have energy flexibility concerns due to grid systems (Welton, 2017). Further, few studies associate spatial data specifically with policy outcomes.

There is some debate on naming and defining energy poverty, and this is often present when discussing **location** of research (Li et al., 2014; Moore, 2012). The reinforcement of data and types of energy poverty studied within certain geographical regions can have long-lasting effects and the perception of energy poverty in the field. Further, study area selection might have an impact on other areas of bias. Previous studies with significant results may lead those variables to be used everywhere, even if not appropriate for the context of the study. Lastly, this illuminates some concepts of publication bias that can be common in many fields, where non-English representation in academic discourse is not voiced (among other biases) (Song et al., 2013). Some of this discrepancy may in part be due to the English limitations of this paper.

The prevalence of spatial visualization over complex **geospatial analytic methodologies** is not surprising given the growth in the application of geospatial approaches to energy poverty policy. Results demonstrate that many analytics are spatially agnostic or do not address spatiality as a driver in the process but as an outcome of the energy system. The most common category, "mapped non-spatial analysis output", indicates the use of location as a secondary attribute to map any analysis or model outputs. For example, mapping an OLS model (spatially agnostic) across census tracts as the observations used in the model. These are often done in studies that include some other form of analysis. For example, Chatterton et al. (2016) mapped the spatial outputs of new energy use data sets released by the UK government to discern patterns of use, in a larger study on household energy use in the UK.

The second most common geospatial methodology is “mapped index”. This deviates from a non-spatial analysis output only in the fact that the creation of an index and inclusion of weighted variables creates an index of energy poverty. These are explicitly selected variables to simplify detection and spatial patterns of a specific form of energy poverty vulnerability. A preeminent example is Walker et al. (2013) who weigh and combine various socio-economic and structural factors to evaluate energy poverty detection in Northern Ireland. This is fairly common in this field most often due to the varied causes and outcomes of energy poverty and the policy needs to simplify the various drivers and indicators of energy poverty in an easy-to-read format.

Spatially explicit analytics, where location is used as a variable, was not commonly used in the reviewed corpus. Applications of methods such as GWR (S. Fotheringham et al., 1998), and Moran’s I analysis (Anselin, 1995; Moran, 1950) enable a better understanding of the explicit impact space has on the distribution of energy poverty. A GWR for example will calculate the relative spatial dependence of observations to optimize the explanatory power of regressions, capturing locally specific model parameters (S. Fotheringham et al., 1998). A Moran’s I calculates the spatial autocorrelation of a given data set, effectively describing both the role space plays in altering assumptions of linear models, but also allowing for a description of local variations of the outcomes of the model (Anselin, 1995; Moran, 1950). For example, Robinson et al. (2018) use a Geographically Weighted regression to incorporate explicitly spatial terms into a comparative analysis of energy poverty indicators in the UK. While lacking currently, spatial analysis methods have the potential for wider adoption in the energy poverty field simply due to the relative age of the field and geospatial analytics. As more spatial analytics are developed, and more spatial energy data is becoming available, the frequency and applicability of these methods could increase.

Taken in combination, some collected variables provide patterns that highlight potential bias in the field. Energy poverty pathways showed a consistent reliance on government datasets and census-level spatial units (Table 2.8). This finding suggests that the structure of available data may skew how energy poverty is defined and recognized. Government-sourced data is overall the main source of data and is the main source in the UK and the US-based studies. Cross-tab analysis demonstrates that while spatial variable use and data sources seem idiosyncratic, larger patterns are emerging both in terms of how they are used to operationalize energy poverty pathways and how data access may play a role in the locations of geospatial energy poverty work (Table 2.8). Single sourced data can be harmful to fields in general and can become standard within the body of work. For example, the 2020 US Census systematically undercounted the US population, while also under-representing groups vulnerable to energy poverty (Cramer, 2022). Continuous use of this data for decisions around energy poverty has the possibility of misrepresenting spatial energy poverty, preventing resources from being allocated as needed.

Further, we see evidence of potential bias between locations of research and spatial data sources. Results were rarely if ever, triangulated with findings from researchers, non-profits, community-driven, or private data collection. Data triangulation is using data from multiple sources, scales, or methodologies to complement or verify results. Triangulation can lead to validation through convergence or unearth tensions across scale or source when it diverges, highlighting areas requiring further analysis (Nightingale, 2016). Researchers' overreliance on the structure of available data may also skew how energy poverty is defined and recognized. If left unexamined, a strong bias towards free data sets can contribute to scale confusion and limit opportunities for data triangulation. Scale confusion is a combination of multiple factors, as scale can be defined in a multitude of ways. Generally, a scale can describe the literal geographical extent of a phenomenon (i.e. census tract scale) or describe the scale of a process occurring over space. One confusion is that the scale of analysis is not always appropriate to the policy addressed. For example, unlike a US state, a census tract is not a policy entity. The use of census tracts (and smaller geographies) allows for efficient analysis but is not the spatial frame through which a policy decision is enforced. Other bounding geographies such as US States or incorporated towns may provide a better spatial scale for addressing energy poverty if the research requires it. Another confusion is a mismatch in the scale of processes. This is more commonly addressed in energy poverty due to how many iterations of energy poverty pathways there are. For example, household decisions and the pricing of electricity are both processes that contribute to energy poverty in some way. However, they are existing at different scales, under different policies, and interact with other processes. Diversifying sources of data and locations of analysis, as well as the sources of the data, can provide a way to triangulate the knowledge, verifying the efficacy of patterns found, intervention success, and overall attempting to clarify scale confusion.

While the theoretical implications of spatial data are discussed in energy poverty (Bouzarovski & Simcock, 2017), there is also quantitative work starting to form an academic path towards a triangulation approach for energy poverty. Robinson Lindley, and Bouzarovski (2019) used a mapped principal components analysis (PCA) of energy poverty vulnerabilities to compare to a geospatially weighted PCA of the same data, identifying areas of agreement and disagreement when space is considered a driver of vulnerability. Another avenue is to use the same data and compare policy outcomes, identifying contradictions in the applied analysis used for detection (Robinson et al., 2017; Walker et al., 2013).

Recommendations

This review is limited to spatially specific studies published in the English language. Although this is the international standard for scientific communication, it has the potential to undervalue essential contributions to spatial analytic research in the energy poverty space being communicated in other languages (Konno et al., 2020). Decisions around categorization were made with previous knowledge of the energy poverty field, but are subject to the influence of researcher positionality.

As a field, energy poverty encompasses a variety of different methods, definitions, and metrics. The impact of using space as a part of energy poverty analysis is directly tied to the call to spatialize energy justice Bouzarovski and Simcock 2017). Spatial analytics bring the promise of more nuance to identifying and defining energy poverty. Methods like GWR have the potential to provide context to social and physical interactions that can inform policy and provide clarity about why policy successes in one region may not translate to all others. However, geospatial data can also provide its own set of equity-relevant considerations. The goal of energy justice is to make sure people can live comfortably as they see fit and therefore poverty research is a field with an end goal.

Recommendation 1 – Scale

Use multiple scales of data in energy poverty research

Ideally, energy poverty research should be performed with multiple scales of data to conceptualize the issue in a frame that limits spatial energy justice issues. If needed, single scales used in analyses must align with the goals of the study and must also recognize the limitations. The use of spatial analysis should help provide novel ways to understand energy poverty, not hinder its detection.

The results of the review showed an overwhelming majority of papers used data at the census/voting boundary. This is often the scale at which the lowest resolution data is available in high quality. While this is often unavoidable, the use of multiple scales of data in analysis can provide a systematic scalar data triangulation. Specifically, verification of energy poverty patterns at multiple scales or recognition of inconsistencies between scales are highly useful and an opportunity for further research. For practitioners, this provides a broader coverage of possible experiences of energy poverty, increasing at the very least a recognition of possible avenues forward. Some studies have produced multi-scalar studies that provide a good baseline for attempting multi-scalar work, including Morrison and Shortt (2008) who use multiple scales of analysis to highlight inconsistencies in targeting fuel poverty between household and census designations.

Recommendation 2 - Data source

Increase reporting standards and open-source data sharing.

Enact ways to increase available data and share it between governments, nonprofits, researchers, and more. One way to accomplish this is through increased data reporting standards and open-source data releases to improve data availability in the field. Data used for energy poverty often has multiple aspects of privacy concerns that prevent it from being shared widely. This is the case, especially with the energy use information that is needed, but demographic data, treatment data, and health data are all part of this pattern. The results of this work showed an overreliance on government-sourced, census-level data. Focusing collection of data that can be shared for everyone to use cheaply and effectively allows for data triangulation - validating or illuminating patterns of energy poverty. This is especially true for addressing the combination of household survey data, which allows for nuanced views of personal experiences of energy poverty with large-scale demographic data on energy poverty. This can be accomplished first by sharing the scale and source of data used in research and applied work. If possible, data should also be shared for use in other contexts. Second, as utilities, cities, and academic institutions are developing new ways to collect household data, innovative policies around sharing data must be addressed. The ability to share data between entities is a step in moving towards an approach that incorporates multiple parts of energy poverty.

Recommendation 3 - Gaps

Focus research on geographies and scales that have not been accomplished, and focus research on understanding how people may be missed.

While being novel is the aim of all research, there should be a focus on spatial energy poverty research to fill in the gaps and continually contextualize energy poverty moving forward. In particular, there is a gap in understanding both how the biases in spatial research might affect outcomes, and more broadly, an opportunity to use geospatial methodologies to fill these gaps. Some examples include steps forward include:

- Creating and sharing large scale household survey data for spatial use

- Spatially explicit comparative analysis of spatial energy poverty across different locations, scales, and, data sources
- Multi-scale analysis of energy poverty
- Multiple data sources in single studies.
- Incorporate concepts of the geography of policy in addressing energy poverty.
- Developing methodologies for identifying common patterns of misidentification or bias.

Some of the studies from the reviewed corpus are good examples of how to accomplish some of these areas. Beyond Morrison and Shortt (2008) using multi-scalar analysis, Graff et al. (2021) developed a survey methodology to collect data from several houses in Indiana to understand energy poverty trends. Robinson et al. (2017) map policy designations to compare the inequity in spatial patterns of energy poverty interventions. Mashoodi et al. (2019) explicitly frame spatial patterns as a spatial energy justice concern, focusing on the spatial patterns of indicators as a way to understand how to address energy poverty across a country.

In summary, the use of spatial analysis and spatial data brings a different set of challenges to researchers and practitioners as the spatial lens is effective at hiding and illuminating trends, both spatial and theoretically. More work is required to fill gaps in understanding through a recontextualization of spatial analysis as a spatial energy justice issue. Bias is inevitable in academic research, but continued integration of bias may move the field away from critically examining already common practices. Energy poverty research has walked the line between trying to define energy poverty and use for identifying and intervening. The research presented here surveys the recent spatial energy poverty analysis to highlight the trends that are emerging as the field grows. As the field moves forward, addressing these biases is at risk of incorporating unjust practices and unjust outcomes. Energy poverty research as a field seeks to change lives for the better and this work will help bring the solutions to fruition.

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Supplementary Information

Table 2.11

Reference papers for semi-systematic review

Verification publications
Bednar, D. J., Reames, T. G., & Keoleian, G. A. (2017). The intersection of energy and justice: Modeling the spatial, racial/ethnic and socioeconomic patterns of urban residential heating consumption and efficiency in Detroit, Michigan. Energy and Buildings, 143, 25–34.
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Walker R, McKenzie P, Liddell C, Morris C (2015) Spatial analysis of residential fuel prices: Local variations in the price of heating oil in Northern Ireland. Applied Geography, 63:369–379.

Table 2.12

Final review corpus

#	Name	Citation
1	*A Geospatial Assessment of Small-Scale Hydropower Potential in Sub-Saharan Africa*	(Korkovelos et al., 2018)
2	*Area-based targeting of fuel poverty in Northern Ireland: An evidenced-based approach*	(Walker et al., 2012)
3	*Articulating strategies to address heat resilience using spatial optimization and temporal analysis of utility assistance data of the Salvation Army Metro Phoenix*	(Zhao et al., 2020)
4	*Assessing population vulnerability towards summer energy poverty: Case studies of Madrid and London*	(Sanchez-Guevara et al., 2019)
5	*Assessing the energy justice implications of bioenergy development in Nepal*	(Damgaard et al., 2017)
6	*Continental-scale assessment of the African offshore wind energy potential: Spatial analysis of an under-appreciated renewable energy resource*	(Elsner, 2019)
7	*Distributional disparities in residential rooftop solar potential and penetration in four cities in the United States*	(Tony G. Reames, 2020)
8	*Distributional justice in Swedish wind power development - An odds ratio analysis of windmill localization and local residents' socio-economic characteristics*	(Liljenfeldt & Pettersson, 2017)
9	*Domestic energy mapping to enable area-based whole house retrofits*	(Gupta & Gregg, 2020)
10	*Double energy vulnerability: Spatial intersections of domestic and transport energy poverty in England*	(Robinson & Mattioli, 2020)
11	*Enabling a just transition: A composite indicator for assessing home-heating energy-poverty risk and the impact of environmental policy measures*	(Kelly et al., 2020)
12	*Energy poverty and gender in England: A spatial perspective*	(Robinson, 2019)
13	*Energy Poverty and its Spatial Differences in Nigeria: Reversing the Trend*	(Sanusi & Owoyele, 2016)
14	*Energy poverty risk mapping methodology considering the user's thermal adaptability: The case of Chile*	(Pérez-Fargallo et al., 2020)

Table 2.12 (continued)

15	*Energy poverty vulnerability index: A multidimensional tool to identify hotspots for local action*	(Gouveia et al., 2019)
16	*Estimating fuel poverty at household level: An integrated approach*	(Walker, McKenzie, et al., 2014)
17	*Evaluating fuel poverty policy in Northern Ireland using a geographic approach*	(Walker et al., 2013)
18	*Examining the relationship between energy poverty and measures of deprivation*	(Marchand et al., 2019)
19	*Fuel poverty in Scotland: Refining spatial resolution in the Scottish Fuel Poverty Indicator using a GIS-based multiple risk index*	(Morrison & Shortt, 2008)
20	*Geographic and socio-economic barriers to rural electrification: New evidence from Indian villages*	(Dugoua et al., 2017)
21	*'Getting the measure of fuel poverty': The geography of fuel poverty indicators in England*	(Robinson et al., 2017)
22	*Land surface temperature and energy expenditures of households in the Netherlands: Winners and losers*	(Mashhoodi, 2020)
23	*Lighting the World: the first application of an open source, spatial electrification tool (OnSSET) on Sub-Saharan Africa*	(Mentis et al., 2017)
24	*Local and national determinants of household energy consumption in the Netherlands*	(Mashhoodi et al., 2020)
25	*Mapping electricity affordability in Brazil*	(Piai Paiva et al., 2019)
26	*Mapping fuel poverty in Portugal*	(Simoes et al., 2016)
27	*Mapping household direct energy consumption in the United Kingdom to provide a new perspective on energy justice*	(Chatterton et al., 2016)
28	*Mapping the energy performance gap of dwelling stock at high-resolution scale: Implications for thermal comfort in Portuguese households*	(Palma et al., 2019)
29	*Multidimensional index of fuel poverty in deprived neighbourhoods. Case study of Madrid*	(Martín-Consuegra et al., 2020)
30	*Poverty reduction through photovoltaic-based development intervention in China: Potentials and constraints*	(Liao & Fei, 2019)
31	*Predicting fuel poverty at a small-area level in England*	(Fahmy et al., 2011)

Table 2.12 (continued)

32	*Residential solid fuel use: Modelling the impacts and policy implications of natural resource access, temperature, income, gas infrastructure and government regulation*	(Fu et al., 2014)
33	*Residual Inequity: Assessing the Unintended Consequences of New York City's Clean Heat Transition*	(Carrión et al., 2018)
34	*REST framework: A modelling approach towards cooling energy stress mitigation plans for future cities in warming Global South*	(Bardhan et al., 2020)
35	*Spatial analysis of residential fuel prices: Local variations in the price of heating oil in Northern Ireland*	(Walker et al., 2015)
36	*Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension*	(Mashhoodi et al., 2019)
37	*Targeting and modelling urban energy retrofits using a city-scale energy mapping approach*	(Gupta & Gregg, 2018)
38	*Targeting energy justice: Exploring spatial, racial/ethnic and socioeconomic disparities in urban residential heating energy efficiency*	(Tony Gerard Reames, 2016)
39	*The intersection of energy and justice: Modeling the spatial, racial/ethnic asocioeconomic patterns of urban residential heating consumption and efficiency in Detroit, Michigan*	(Bednar et al., 2017)
40	*The socio-demographic and geographical dimensions of fuel poverty in Italy*	(Besagni & Borgarello, 2019)
41	*The Spatially Varying Components of Vulnerability to Energy Poverty*	(Robinson et al., 2019)
42	*Underrepresenting neighbourhood vulnerabilities? The measurement of fuel poverty in England*	(Robinson et al., 2018)
43	*Unequal resilience: The duration of electricity outages*	(Liévanos & Horne, 2017)

CHAPTER 3: SCALE AGNOSTIC AND SCALE SPECFIC INDICATORS OF VULNERABILITY TO ENERGY POVERTY

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Abstract

Energy poverty describes the disproportionate financial burden of access to heating, cooling, and other essential energy uses. And In the US, energy poverty results from many distinct combinations of demographic and built environment characteristics that affect energy cost and total use. But current US energy poverty policy, such as the Weatherization Assistance Program (WAP), defines eligibility for assistance using simplistic parameters, such as income. This has the unintended consequence of misidentifying or excluding households with unique energy poverty patterns. We suggest that spatial analysis is key to reducing energy poverty in a way that supports a justice-centered change to energy poverty policy.

This paper addresses this concern by using spatial analysis to address spatial energy justice and apply it to current US energy poverty policy. Using data from North Carolina, USA, we identify sets of co-occurring energy poverty characteristics using Principal Components Analysis (PCA) at three geographic scales: the community action agency scale, county scale, and census tract scale. Results differentiate nine energy poverty signatures based on unique co-occurrences of demographic and built environment characteristics that contribute to the likelihood of energy poverty. We detected "scale-agnostic" energy poverty signatures which appeared at all three scales of analysis as well as "scale-dependent" signatures, which did not appear at all three scales. The presence of scale-dependent signatures suggests single-scale spatial analyses has the potential to dismiss particular forms of energy poverty. A geographically weighted PCA was then performed to identify the extent that which a state-wide approach to setting implementation criteria creates inequities due to location dependence in each energy signature. The results indicate localized geographic influences undetectable by a global PCA. Applied to the frame of WAP eligibility and distribution criteria, the spatial and location-

dependence observed in this study suggests applying locally specific eligibility criteria that are sensitive to prevalent energy poverty signatures to promote equity.

Keywords GIS, PCA, Energy Poverty, GWPCA, Scale, North Carolina

Introduction

Energy poverty results from many intertwined socio-technical systems (Baker & Beer, 2007; Day & Walker, 2013; Harrison & Popke, 2011; Jenkins et al., 2014). One of the most used academic definitions of energy poverty is the "inability to attain a socially and materially necessitated level of domestic energy services" (Bouzarovski & Petrova, 2015). The broadness of this definition recognizes that the need for energy services is universal, but the circumstances surrounding the experience of energy poverty can vary due to geography, environments, and human behaviors (Bouzarovski & Petrova, 2015). The multitude of ways through which energy poverty may be experienced has led to energy poverty being viewed through a vulnerability lens, as the exact causes of energy poverty often remain hard to disentangle (Mould & Baker, 2017; Thomson et al., 2017). Recent work has used spatial data related to energy poverty to highlight the patterns of energy poverty, related vulnerabilities, and energy infrastructures to contextualize energy poverty experiences.

While increasing the capability to understand spatial patterns of energy poverty metrics (Bouzarovski & Simcock, 2017), geospatial studies of energy poverty are unable to fully capture systematic connections and understand the justice implications of energy poverty (Herrero, 2017). Policy addressing energy poverty is directly tied to geographic boundaries larger than the household level, where energy poverty occurs. For example, federal funding for energy poverty is often allocated to the states based on need (Bednar & Reames, 2020). Further, analyses are often performed at different geographic scales for different policy or intervention programs (i.e. at the county level in one state and the state level in another). This leads to a lack of clarity within spatial energy poverty research and policy on the proper metrics to use when targeting energy poverty.

These outcomes are justice issues, directly tied to both *energy justice* and s*patial justice*. Energy justice focuses on the unequal distribution of benefits and burdens of the energy field across all populations and the environment (Hernández, 2015; Jenkins et al., 2014). Spatial justice focuses broadly on location as a driver of just outcomes and experiences of any process (Bouzarovski & Simcock, 2017; Soja, 2010). The consideration of the spatial justice implication within energy justice framing, what we are terming spatial energy justice, has been broached in energy poverty literature (Bouzarovski & Simcock, 2017). But little work has framed applied spatial analysis through the lens of spatial energy justice and what outcomes might look like for a more spatial just energy landscape. This work frames the use of spatial analysis of energy poverty as a potential pathway to inform spatial energy justice, both as a methodological advancement for the field and through use in policy.

This research uses spatial analysis to identify the inconsistencies of energy poverty identification that may occur when framed through individual geographic scales and locations. Using the US state of North Carolina as a study site, this study incorporates aspects of energy vulnerability identification, what we term *energy poverty signatures,* with spatial analysis to provide an exploration into the role of geographic scale in energy poverty identification. Currently, there is no systematic spatial methodology linking spatial energy justice to energy poverty. We discuss the implications of these findings for just and sustainable energy poverty policy through the lens of the Weatherization Assistance Program (WAP), a US federal program that funds energy efficiency improvements and has recently seen an increase in funding through the 2021 US infrastructure bill (Infrastructure Investment and Jobs Act, 2021). First, a set of principal components analyses (PCA) were performed using energy poverty vulnerabilities at three geographic scales: state, community action agency (CAA), and county to identify how energy poverty changes. Energy poverty vulnerabilities describe the likelihood of experiencing a specific type of energy poverty at any given time at a given location (Thomson et al., 2017). Using the PCA method, I characterize signatures as *scale-dependent*, present at a singular geographic scale, or *scale agnostic*, present at all geographic scales of analysis. Second, a geographically weighted principal components analysis will be performed to understand the regional influence of energy poverty vulnerabilities beyond a statistically global analysis. The overall objective of this paper is to model the capability of locally specific spatial analysis to determine the location of energy poverty signatures and at what geographic scale they occur to address spatial energy justice concerns in policy interventions.

Background

On November 15th, 2021, Present Biden signed into law a nearly $1 trillion infrastructure bill (Infrastructure Investment and Jobs Act, 2021). While the bill focused on a wide range of infrastructure policies in the US, it allocated more than $3.1 billion to the federal Weatherization Assistance Program (WAP) to buoy the capacity of the program to increase efficient housing stock (Brierton, 2022). WAP money is allocated to each state based on a formula of the previous allocation of funds coupled with climate, population, and energy burden variables (NASCSP, 2019). North Carolina will receive an estimated $90 million additional funds for WAP improvements, which is allocated to the over 30 CAAs in the state (Brierton, 2022). A community action agency (CAA) is a non-profit organization that receives federal funding from the US government to address a variety of poverty-related issues in the US. In North Carolina, they are the main awardee for WAP funds. They often serve a single or collection of counties in NC (Tazewell et al., 2019). The formula for allocation of weatherization funding to CAAs in NC is split, with 51% of the allocation based on households in poverty compared to the total in NC, and 49% based on the number of homes weatherized in the previous fiscal year in the CAA. In North Carolina, households below 200 percent of the federal poverty line are eligible to apply for WAP, with priority given to individuals with disabilities, the elderly, families with children, and high-energy burdens (NCDEQ, 2022). Further, applicants must own the home or have written permission from the owner to apply. Typically, a home audit identifies areas of most need within the dwelling. In some cases, a weatherization may not be completed due to the poor condition of the home. Examples of this include a leaky roof or dry rot, which means houses in extremely poor conditions will not be weatherized.

As a federal program addressing a social need, the WAP contends with a variety of justice issues. It is a program that targeting inequity in housing efficiency and energy access, while also attempting to distribute funds to those in need. How and if the WAP program equitable distributes these funds is not always clear. In January 2021 President Biden signed an executive order directing environmental justice to be a major commitment of federal programs addressing the climate crisis in the US (The White House, 2021). Specifically, the Justice40 program aims to define actions to direct 40% of funds to disadvantaged communities (DOE, 2022). These include screening measures for communities based on a variety of common social disadvantages, such as income, race, and housing structure. While WAP is part of the initiative covered as an energy efficiency program, it is by the definition of the Justice40 program, addressing communities in need. Geography is defined as a major component of the DOE's work into addressing energy injustice, as census tracts are the boundary used to identify communities in need. However, there is no substantive link made between just allocation of funding and spatial patterns of allocation. This work moves attempts this by marrying the geographies of detection and fund allocation with the goal of a just implementation of federal policy.

Specifically, addressing the spatial and energy justice component of WAP to rethink the implementation of the program in a just way in NC.

Energy efficiency is only one element of energy poverty. While energy poverty is defined to incorporate the multitude of experiences that it might entail, this leads to difficulty in detecting and intervening when a household experiences more than one type of vulnerability. A household's vulnerability to energy poverty can often be split into two distinct groups: a built environment group, which focuses on the structure of the households, and a socio-demographic group, which focuses on the human occupants of households (Reames, 2016). Examples of energy poverty factors of the built environment include home efficiency (Kontokosta et al., 2020; Lewis et al., 2020), fuel type (Howard et al., 2012; R. Walker et al., 2014), house age, and house type (Graff et al., 2021), and utility efficacy (Liévanos & Horne, 2017; Oppenheim, 2016). These infrastructure components contribute to complex spatial patterns of energy poverty, where, for example, an older house is not energy efficient and can create compound demands/stresses for residents. Human social vulnerability to energy poverty is used to define socio-demographic characteristics of homeowners that make them susceptible to energy poverty Examples include race (Bednar et al., 2017; Harrison, 2016), income (Harrison, 2017; Reames, 2016), and disability (Hernández, 2015; Snell et al., 2015). Socio-demographic studies of energy poverty are common, and many use geographies to identify spatial patterns (Bednar et al., 2017; Robinson et al., 2019; R. Walker et al., 2013, 2015). These studies are often focused on how the actions and characteristics of a person may drive energy poverty. Found in both groups, policy often considers the decisions and laws made by legislatures at all levels to aid in energy poverty with the interaction between socio-economic and the built environment. This includes legislation such as energy pricing (O′Connell et al., 2014), assistance programs (Murray & Mills, 2014), utility providers (Harrison, 2013b), and energy laws (Welton, 2017).

Energy justice is a broad term that applies social equity concepts across all parts of the energy sector, including policy, production, and consumption (Buechler & Martínez-Molina, 2021). Energy justice is concerned with the whole energy system, specifically accounting for where injustices emerge, which parts of society are ignored, and how actions are taken to alleviate inequities (Jenkins et al., 2016). These concerns are framed in three key aspects of justice: distributional, recognition, and procedural justice. Distributional justice is concerned with where the processes and outcomes of energy exist and their unequal outcomes. Recognition deals with understanding that identification and lack thereof of energy issues (such as energy poverty) create inequalities. Procedural justice implicates the political process by which energy issues are undertaken, and where injustices arise (Jenkins et al., 2016). Justice as a concept within energy then is recognizing that the systems of creating and delivering energy, and the act of using energy itself all can create unjust energy practices (Sovacool et al., 2017). Broader implications of energy justice have moved the concept away from simply technological, and into the social, where inequalities for socio-technical systems can be recognized and addressed. Jenkins (2018) provides a strong case for the uniqueness of energy justice that gives it strength in the concept of being used as a political tool. These specifically include the recognition of energy justice coming from a strong applied and academic tradition, is not inherently anti-establishment, and is focused on a systematic outcome (energy production and delivery) as opposed to a broad idea of something like social justice. While this is neither inherently good nor bad, these factors can lead to acceptance in political forums. In this way, energy justice can be used as a framework for both an analysis of an outcome and a tool for developing new pathways for energy equality.

It is well understood that energy poverty is a geographically uneven phenomenon (Bouzarovski & Simcock, 2017). Because energy poverty (and many other socially constructed phenomena) occurs at different rates in different locations, there are often considered issues of spatial justice (Soja, 2010). Spatial justice as an outcome refers to the focus on the unequal distribution of resources, material or otherwise, that result from the uneven processes of social, economic, and political relations (Dikeç, 2009). Existing spatial structures, such as economic, social, and physical patterns, contribute to and reproduce injustice through space.

The call for spatial justice in the inclusion of energy poverty work comes from the recognition that energy poverty is in part driven by structures and processes that are spatially varying, and the outcomes of the energy system arbitrarily disadvantage certain locations over others (Bouzarovski & Simcock, 2017). Thus, understanding energy poverty as an injustice requires a framework that addresses the spatially varying process that drives it. Spatial justice comes out of the work of Iris Marion Young (1990) and David Harvey (1973, 1996) and was codified by Edward Soja (2010) in *Seeking Spatial Justice*. The concept of spatial justice posits that injustice stems from "the spatial" as a process, where space is continually changing and redefines itself as an actor in the broader frame of social justice. Dikeç (2009) built upon Soja's work framing the "injustice of spatiality" as the concept that space is a process in political, economic, and social structures to continually create uneven spaces. Realistically, this means that it is hard to untangle the aspects of social inequality at any given time. But framing these inequalities around their spatial structure can begin to open spaces to understand the processes occurring there. Further, Soja contends justice is a multi-scalar phenomenon, occurring beyond what is seen at the local. Framing justice issues in this way understates the unjust outcomes of systems. Injustices occur within scales and in the context of other scales. Therefore, spatial justice as an outcome refers to the focus on the unequal distribution of resources, material or otherwise, that result from the uneven social, economic, and political processes. Dikeç describes how existing spatial structures (economic, social, and physical) contribute to and reproduce injustice through space. In other words, through the injustices of spatiality, these processes produce unique and spatially salient injustices that can only be deciphered through a complete analysis of the forms, functions, and processes that build and reproduce injustice.

In 2017 Bouzarovski and Simcock published *Spatializing Energy Justice* (2017). This work provides a vital overview of the concepts of energy justice as they are viewed through the lens of spatial justice as conceptualized by Soja (2010). This work argues that the outcomes of the lived energy experiences are often viewed in the inequity of a specific socio-economic or demographic group in a specific area, and not the systematic inequities that drive the inability to access energy as needed. Spatial outcomes are based on group indicators, not underlying spatial drivers and justice considerations driving energy poverty. The call to action is to make a concerted policy effort to recognize where people are disenfranchised, how that process is realized and the political structure surrounding those experiences must be accounted for, all in a spatially explicit frame. This can be addressed through a multi-scalar approach that incorporates the main mechanisms of justice, distributional, recognition, and political discourse, that hinders access to energy. The authors argue that energy poverty detection must be improved to detect injustice in this context and those true solutions will come from prioritizing resiliency at multiple scales. For this paper, we use the term spatial energy justice to identify the combination of spatial and energy justice that frames the following work. Spatial energy justice provides a foundation to understand how spatiality alters energy poverty experiences. In this paper, we will focus on scale and location, both identified in energy justice and spatial justice literature as specific frames through which spatial energy justice is altered.

The identification of energy poverty locations through spatial means has been performed many times in energy poverty literature. Most often, these studies use a simple, yet powerful technique of mapping indicated vulnerabilities to identify areas of increased probability of energy poverty (Randall Lit Review Forthcoming). Recently studies have begun to focus on spatial analysis techniques as a tool for identifying energy poverty in a spatial context (Bednar et al., 2017; Reames, 2016; Robinson, 2019; Robinson et al., 2017, 2019; R. Walker et al., 2013, 2015). However, these are often work focusing on a singular scale of analysis using publicly available data, limiting patterns that might be observed at other scales in comparison.

In energy poverty work there is some focus on the impacts of performing analysis at different scales, particularly with a focus on the socio-political processes embedded in energy development and distribution that take forms at different scales (Bouzarovski & Simcock, 2017; Bridge, 2018; Horner et al., 2011; Sareen et al., 2020). However little work focuses on quantifying the impacts of using data at different scales, or their interaction between scales. This is due in part to the lack of availability of granular data (Reames, 2016). Access to data on a household scale provides a more complete understanding of the local variability of energy poverty (Reames, 2016), and individual household data provides the ability to analyze small-scale differences. However, the lack of availability at small scales means aggregated data is used for analysis and which leads to a scalar discrepancy of data (Fotheringham & Rogerson, 2009; Openshaw, 1984).

While not an explicitly spatial analysis, PCA is commonly used to derive social vulnerability indexes (Cutter et al., 2003; Stafford & Abramowitz, 2017) due to its ability to reduce complexity in a relatively easy-to-understand output, particularly when mapped. It has also been used to derive energy poverty vulnerability signatures (Robinson et al., 2019) and to compare the effects of scale on the data reduction process (Griffith et al., 2000). Further, there has been an increase in studies implementing a spatial-specific form of PCA, a geographically weighted PCA (GWPCA) (Harris et al., 2011, 2015). GWPCA explicitly identifies how location drives outcomes of social and environmental processes (Chen et al., 2021; Kallio et al., 2017; Tsutsumida et al., 2017; Wei et al., 2016). This has increased with the recognition of location as an influential and embedded condition in both human and environmental processes. In energy poverty work specifically, a GWPCA has been used by Robison et al. (2019) to identify locally specific indicators of energy poverty in England. However, the use of intra-scalar analysis with a PCA on energy poverty analysis has not been performed.

Energy poverty is an evident pattern and policy concern in NC, where racial legacies of energy development have led to infrastructural and socio-demographic energy injustice (Harrison 2013a). There are unique trends in North Carolina lending it as a useful study area for energy poverty and a valuable case study for a multitude of factors influencing energy poverty. North Carolinians consume electricity at 18% higher than the US average and some areas pay extremely high rates (Harrison, 2013a). Further, many NC residents live in mobile homes, which are prone to energy poverty in both the winter and summer months. (Harrison & Popke, 2011; Kovach et al., 2015) Many stages of energy infrastructure development in North Carolina were directly tied to race and the urban-rural divide (Harrison, 2013b, 2015, 2017). The processes of energy development in North Carolina led to structural aspects, such as power lines, being developed in a spatially unjust way, and allowed for rural, poor, and majority Black areas to bear the cost of failed energy production (Harrison, 2013b). These legacies have created a fractured energy landscape in North Carolina, particularly with energy providers. There are 111 utility providers in North Carolina (Figure 3.1D). Over 4 million accounts are serviced by 3 investor-owned utilities: Duke Energy Progress, Duke Energy Carolinas, and Dominion North Carolina Power (Figure 3.1D). The remainder of North Carolina residents are serviced by 32 electric membership cooperatives and 76 municipal utilities (NCUC, n.d.).

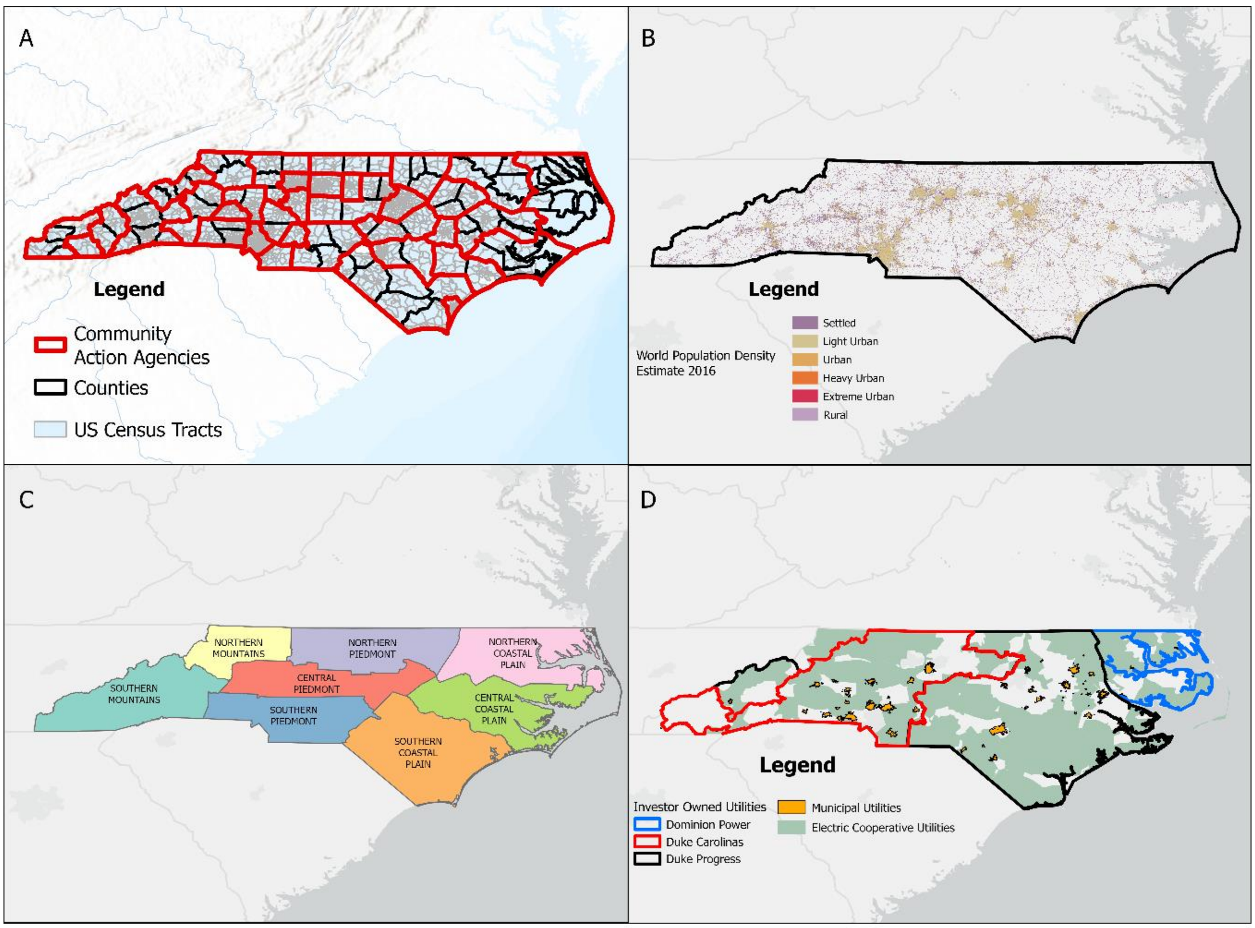
Energy poverty is a spatial phenomenon, and location drives how energy poverty is experienced. While research has engaged with North Carolina energy poverty at the household level, little is known about the spatial trends of energy poverty across the state and the geographical scale at which energy poverty signatures are present. Previous work has also defined methodologies for deriving energy poverty signatures at a given geographical scale to better understand the complex nature of energy poverty. This work will merge a US-focused study area and multi-scale methodologies to understand both the locational and scalar change energy poverty signatures experience. This is a direct policy need. One solution at one scale – such as one broad statewide policy – ignores multiple historical and systematic disadvantages tied to a location and population. This culminates in a clear gap in the connection between striving for spatial justice and the use of spatial analysis of energy poverty. To that end, this work addresses two specific questions. (1) what energy poverty signatures are present in North Carolina and (2) at what locations and scales are these energy poverty signatures defined? This work will begin to inform spatial justice as a multi-scale frame through which the spatial analysis of energy poverty can be used to delineate signatures from targeting approaches and policy outcomes.

Methods

Study area

Figure 3.1

Research study area, North Carolina referenced in four maps: (A) Reference to spatial scales, US Census Tracts (blue), Community Action Agencies (red outlines), and Counties (black outline); (B) population density (C) Energy Utility providers (D) and NOAA Climate Zones



To identify scale agnostic and scale-specific indicators of energy poverty, analyses were performed for North Carolina (USA), at multiple geographic scales: community action agency, county, and census tract shown in Figure 3.1A. In 2018, the population of North Carolina was approximately 10.3 million, with 71% white, 23% African American, 9.2% Hispanic, and 2% American Indian (U.S. Census Bureau 2019). Approximately 43% of the population lived in unincorporated areas (Cline, 2020).

Heating degree days (HDD) and cooling degree days (CDD) are common measures used to identify energy demands for a given day. The most common calculation of CDD and HDD is the number of degrees the average temperature for a day is above or below 65 F respectively. The North Carolina climate is influenced by the Appalachian Mountains in the west and the Atlantic Ocean along the east, creating three climatic zones. (Fig 1C). The Western Mountains climate is considered a subtropical highland climate while both the Piedmont and Coastal Plain regions have humid subtropical climates (Kunkel et al., 2020). As reported in 2020 the number of HDD per year has decreased in North Carolina overall, with the lowest average occurring over the last 10 years (Kunkel et al., 2020). The number of CDD per year has increased over the past 100 years in NC overall with the highest average in the last 10 years. Higher CDD and fewer HDD indicate that more energy has gone to the increased cooling load in the state, and less to heating.

The number of days of extreme cold has decreased over the past 100 years, while the number of extreme heat days has increased. Increasing heat is more common in the Piedmont and Coastal Plains regions, and cold nights are common in the Western Mountain regions and not the Coastal Plains or Piedmont. However, between 2015 and 2018, each region underwent a climatic shift away from historic norms. In the Western Mountains and Piedmont, the annual temperature increased by 1.1 C (up from historic means of 12.2 and 15.0 C respectively). Annual precipitation increased from 50 to 60 cm in the Coastal Plain (Kunkel et al., 2020)

Overall, 2,653 trillion Btu of electricity was consumed in NC in 2019 with about 696 trillion BTUs of electricity for residential end-use. 10,656 thousand MWh of net electricity was produced in North Carolina in 2019, with 37.5 from natural gas, 29.7 from nuclear, 16.4 from renewables, 16.1 from coal-fired, and 0.1 from petroleum. Houses rely on 4-5 major fuel sources in North Carolina. The most common are natural gas and electricity for heating, at 24 and 64 percent respectively. Propane is 6.6 percent and fuel oil is 2.6 percent. Other sources of heat make up the remaining 2%. Heat sources are near the national average, however natural gas (47.8 percent national average) is much lower and electricity much higher (39.5 percent national average) in North Carolina compared to the national average (EIA, 2021).

Data and Analyses

Data and geographic boundaries were acquired through the R package "tidycensus" (K. Walker & Herman, 2021). In total, 15 data variables were obtained at three geographic scales from the American Communities Survey (ACS) 5-year census (2014-2018) (U.S. Census Bureau, 2019; K. Walker & Herman, 2021). Community Action Agency data was aggregated from county data. Variables include data on households, population, and fuel type linked to energy poverty vulnerability in previous studies. We selected freely available data analytic platforms (R and GeoDa) and data (ACS variables and geographic boundaries), to align the study's procedural transparency and reproducibility with principles of access and transparency.

Two analyses were performed in this study. The first analysis is global principal components analysis (PCA) performed at three geographic scales to identify scale agnostic and scale-dependent energy poverty signatures. The second, a geospatially weighted PCA (GWPCA) was performed at the county and census tract level to find locally-specific energy poverty signatures.

Data were normalized to ratios per unit (community action agency, county, or census block). Each variable was divided by the appropriate unit as designated by the Census Bureau (population, household, housing unit). All data were then transformed using a Box-Cox transformation for irregular distribution and scaled using a Z-score standardization (Robinson et al., 2019; Schmidtlein et al., 2008). This is especially important for a PCA where differences in units and ranges of variability can hinder interpretation (Schmidtlein et al., 2008; Stafford & Abramowitz, 2017). PCA analysis was performed in GeoDa (v 1.14), a spatial statistics platform (Anselin et al., 2006). A PCA was parameterized in GeoDa using singular value decomposition (SVD) and no transformation (as data had already been transformed) at each geographic scale by inputting the standardized data derived from the 15 energy poverty indicators selected. GeoDa outputs contain variable loadings for each component, as well as the proportion of variance explained by the data and the Eigenvalues of the component. Components were retained for observation using the Kaiser Criterion (Anselin et al., 2006; Kaiser, 1960) at Eigenvalue >1.

To understand how a component is represented in a given observation, a component score was calculated. Component scores are the summed variable loadings of the standardized variables at an observation (or geographic location) (Anselin et al., 2006). GeoDa calculates the component loadings for each observation. Mapped, these component scores can be interpreted for spatial patterns.

Next, a robust GWPCA was performed at both census tract and county geographic scales. Community action agencies were not examined in a GWPCA due to a low number of observations. While a global PCA incorporates every observation in the analysis resulting in a singular set of components, a GWPCA uses a set of locally weighted data determined by a kernel to perform a PCA for every observation. This results in the ability to understand how location changes the dimensionality of data and the identification of locally important vulnerability indicators (Harris et al., 2011; Robinson et al., 2019). To perform the GWPCA, the processed shapefiles were analyzed using the GWModel package in Rstats (Gollini et al., 2015; Lu et al., 2014). Centroids for each spatial unit (census block, county) were calculated and a robust GWPA was computed. A robust GWPCA reduces the impact of major outliers in the analysis (Harris et al., 2011). To characterize location-specific indicators of energy poverty vulnerability, I visualized GWModel outputs. Maps demonstrate the distribution of the total variance explained by the model and the variables with the top-loading absolute value component on the first component for each geographic unit.

Energy poverty signatures were interpreted as the component variable loadings at every geographic scale. Signatures could either have positive or negative loading. A set of positive variable loadings and a set of negative loadings of the same component may be considered two different energy poverty signatures, as they are not combined into one signature. Signatures were deemed the same across a scale if the variable loadings for the same set of variables were over 0.25. Interpretation, or naming, of the signatures was based on the loadings within the signature. Once signatures were identified for each spatial scale and analyzed to compare if they were similar across multiple scales as defined in the previous section, 3 scalar patterns were identified for each signature. “Scale-agnostic” is used to define energy poverty signatures that are present at all geographic scales of analysis. “Scale-specific” is used to define signatures that are only present at one spatial scale. “Partially scale agnostic” is defined as signatures that were present in two of the three spatial scales analyzed.

Results

Table 3.2, Table 3.3, and Table 3.4, found in the appendix, show descriptive statistics for all 18 variables used in the PCA and GWPCA analyses at three aggregation scales. The average census tract area in North Carolina is 58.4 km2 with a maximum of 1,829 km^2 and the smallest at 0.48 km^2. There were, on average, 1,785 households, 2,083 housing units, and a population of 4,626 in each census tract. The average county area in North Carolina is 1,286 km^2 with a maximum of 2,473 km^2 and the smallest at 458 km^2. There were on average 39,185 households, 45,730 housing units, and an average population of 101,556 in each census tract. The average CAA in North Carolina is 4,133 km^2 with a maximum of 14,498 km^2 and the smallest at 1,067 km^2. There were on average 118,745 households, 138,577 housing units, and an average population of 307,746 in each census tract.

Individual PCAs were completed for three geographic scales of analysis. The Community Action Agency (CAA) PCA contained 33 observations. Four retained components explained approximately 81% of the variation. The county PCA contained 100 observations. Four components were retained and explained around 74% of the variation. The census tract PCA contained 2164 observations and four components were retained. The four retained components explained around 70% of the variation. All variables with component loadings greater than or equal to + 0.25 or - 0.25 loading were used to aid interpretation. All but one signature considered the “same” between geographic scales had either zero or one contained a different variable loading above 0.25. Signs were used to differentiate between signatures in the same component. Groups of variables loading positively and negatively on the same component were considered two different signatures. A signature with a single variable was considered only once, where the American Indian population loaded above 0.7 in the fourth component of the census tract geographic scale. This was due to the importance of the variable in the study area and the strength of the loading. Other single variable signatures were not considered.

Each principal component at every geographic scale was analyzed to characterize energy poverty signatures. Based on the loading variables show, a total of nine signatures were interpreted across four components and three scales of analysis shown in Table 3.1: socio-economic status, African American renters, SNAP receiving Hispanic and African American Renters, older population using fuel oil heat, older population using LP heat, older homes using non-electric heat, American Indian and African American using LP heat, American Indian population, and African American population using LP heat. Two energy poverty signatures were scale-agnostic or occur at every geographic scale, two energy poverty signatures were partially-scale agnostic, and were similar between county and census tract geographic scales. The remaining five signatures are scale-specific, only present at only one scale.

Table 3.1

Characterized energy poverty signatures identified by the number of scales they occurred at. Descriptions of the signatures are based on the commonly loading variables across the PCAs for each aggregation scale.

Scale characterization	Signature number	Signature Description	Commonly loading variables
Scale agnostic	Signature 1	Socio-economic status	Below HS population disability status present poverty status present mobile home - utility gas use
	Signature 6	Older homes using non-electric heating fuels	Fuel oil heating households older than 1970 utility gas heating - electricity heating use
Partially scale-specific	Signature 3	SNAP receiving Hispanic & African American renters	SNAP benefits rental housing utility gas heat African American population Hispanic population
	Signature 8	American Indian population	American Indian population
Scale specific	Signature 2	African American renters	African American population rental housing electric heat
	Signature 4	Older population using fuel oil heat	Households with residents above 66 fuel oil heating
	Signature 5	Older mobile homes using LP	Households with residents above 66 mobile homes LP gas heating
	Signature 7	American Indian and African American with LP heat	American Indian population African American population LP gas heating -electricity heating
	Signature 9	African American population only using LP heat	African American population LP gas heating Households with residents above 66

Figure 3.2

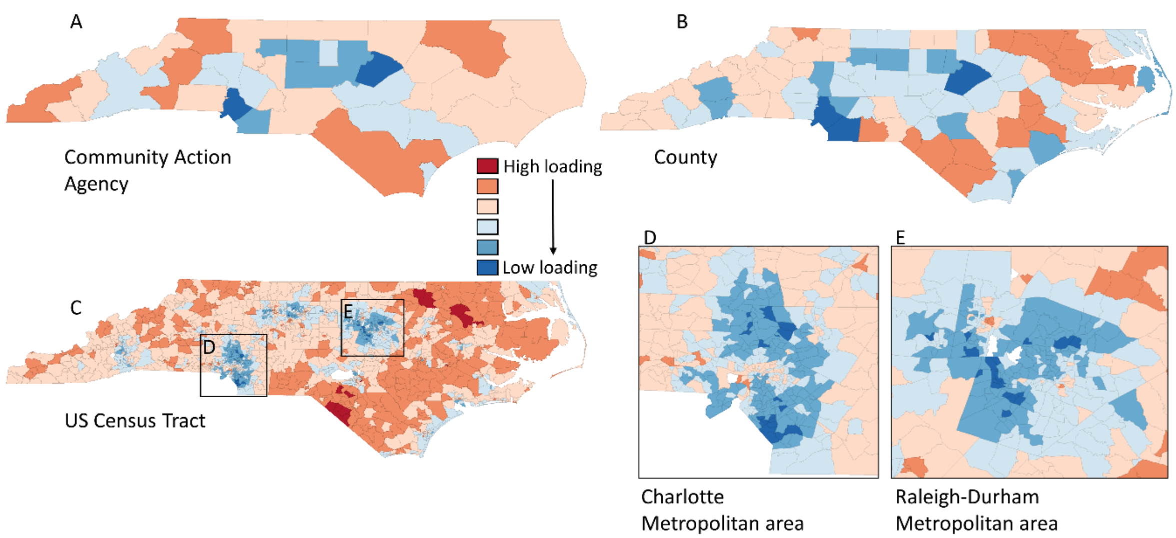
Identified energy poverty signatures for three PCA at each aggregation scale of analysis. Dots represent what component the signature was found in and at what scale.

	signature description	aggregation scale: community action agency	counties	census tract
Component 1	*variance explained*	**45.1%**	**35.5%**	**29.1%**
signature 1	Socio-economic status	●	●	●
Component 2	*variance explained*	**18.0%**	**19.3%**	**22.7%**
signature 2	African American renters	●		
signature 3	SNAP receiving Hispanic & African American renters		●	●
signature 4	Older population using fuel oil heat		●	
signature 5	Older mobile homes using LP			●
Component 3	*variance explained*	**10.9%**	**11.6%**	**10.9%**
signature 6	Older homes using non-electric heating fuels	●	●	●
Component 4	*variance explained*	**7.5%**	**7.5%**	**7.2%**
signature 7	American Indian and African American with LP heat	●		
signature 8	American Indian population		●	●
signature 9	African American population only using LP heat		●	
	Total Variance	**81.5%**	**73.9%**	**69.8%**

Spatial patterns of Signature 1 indicated in Figure 3.3 show a strong urban to rural divide. Charlotte and Raleigh-Durham, the two largest urban areas in NC show low loadings of the signature. Rural areas, particularly in the western portion of the state show very high loadings. Further, the census tract scale shows a much higher spatial variance of the signature. In both urban areas highlighted there are small areas of high signature loading that are not detected by either the CAA or county scale.

Figure 3.3

Signature 1, Socio-economic status, mapped to each geographic scale (A) CAA, (B) County, (C) US Census Tract in North Carolina. Insets from the US Census tract indicate 2 major metropolitan regions in North Carolina, (A) Charlotte and (B) Raleigh-Durham



A GWPCA at the county scale identified local variation in energy poverty signatures using 15 ACS variables and 100 county-level observations. The bandwidth of the GWPCA was selected using automated cross-validation and retained four components in all 100 counties. The nearest neighbor kernel size in robust analysis kernel is 76 and explains between 92% and 95% of the variation. The highest loading variables shifted depending on the county. Variables with the highest loading in one or more counties include disability status, mobile homes, 66+ age, SNAP recipients, houses 1970 and older, and electric heat.

The GWPCA explains more variation in the data than the global county-level PCA. With the reduction of nearest neighbors used in the calculation between the global PCA and GWPCA, both the variance explained increased as well as the variety of top-loading variables on the first component in the study areas. Show in Figure 3.4, the percent of total variance increased to between 92% and 95%. The total number of top-loading variables in the county GWPCA was six and included only disability status and mobile homes from the basic GWPCA. The other four include 66+ age, SNAP recipients, houses 1970 and older, and electric heat.

A GWPCA was run for the census tract scale with 2164 observations. The bandwidth of the GWPCA was selected using an automated cross-validation approach with 4 retained components. The nearest neighbors kernel was 706, a major reduction from 2164 used in the tract global PCA and explained 86-96% of the variation. Variables with the highest loading in one or more tracts include disability status, SNAP recipients, houses built in 1970 and before, and electric heat, rentals, and utility gas heat.

Show in Figure 3.4, spatial results of the county-level GWPCA show a diverse set of top-loading variables across North Carolina. Disability and houses built before 1970 are both common top-loading variables in the western part of North Carolina. The eastern side of North

Carolina has similar characteristics, except occupants 66+ becomes an important variable as well. The east-central portion of North Carolina shows a pattern of electric heat as an important energy poverty vulnerability. This is most likely an absence of electric heating, as that portion of the state has low electric heating levels. Shown in Figure 3.5, the census tract results show a similar slightly different pattern. Western North Carolina is predominantly disability and 66+ as a main top-loading variable, with renters also being a major factor. Further electric heat appears more often and in different locations than was shown in the county issues.

Figure 3.4

County GWPCA results for North Carolina showing percent of total variance explained (PTV) by the GWPCA at every location, and the accompanying top-loading variable for the first component.

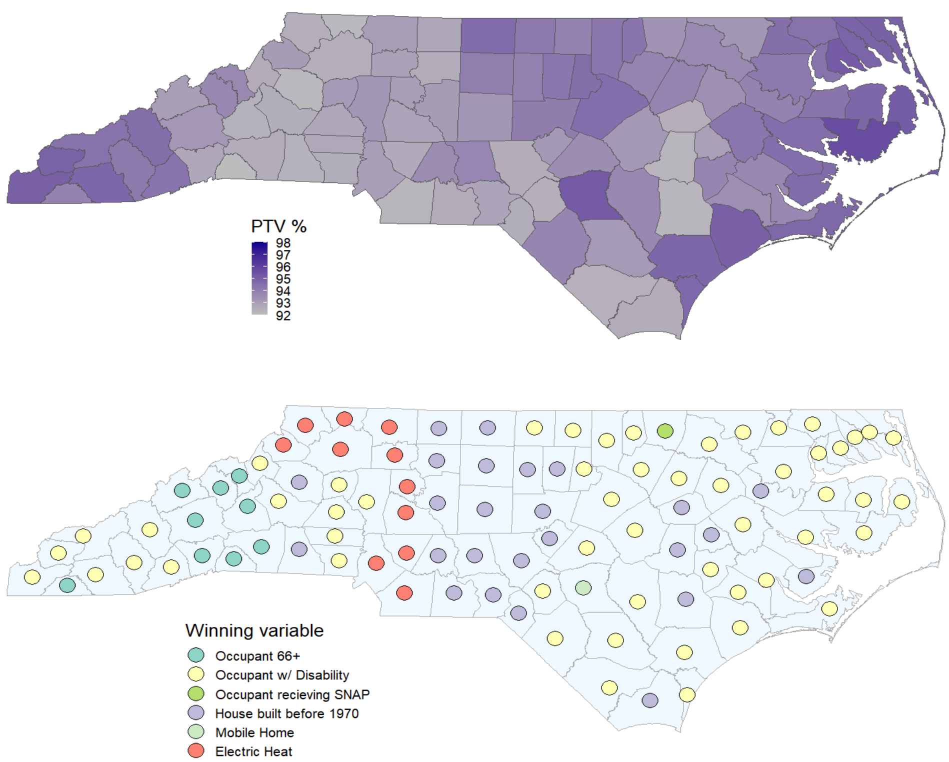
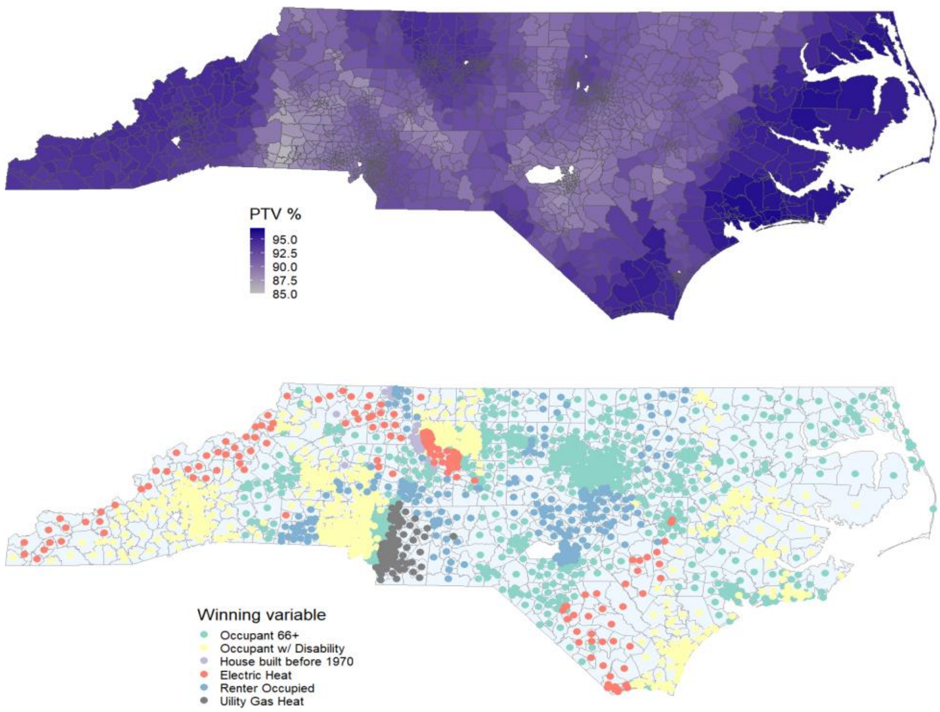


Figure 3.5

Tract GWPCA results for North Carolina showing percent of total variance explained (PTV) by the GWPCA at every location, and the accompanying top-loading variable for the first component.



Discussion

While energy poverty vulnerability indicators are relatively well known (Bouzarovski, 2014; González-Eguino, 2015; Herrero, 2017; Simcock et al., 2018) how they interact or change due to location and scale change is less well known. Understanding patterns of energy poverty signatures as they change between scales is an important step to understanding just energy poverty interventions. The outcomes of this study define energy poverty signatures present in North Carolina, the geographic location of these signatures, and the scalar effects of analysis. This work builds on previous studies exploring the relationship between energy poverty and vulnerability similar methods (Mashhoodi et al., 2019; Robinson et al., 2019) analyzing location, overlapping vulnerabilities, and most importantly geographic scale as they pertain to energy poverty detection. However, this work is novel in its use of scale and PCA combined, analyzing the effect of scale and location on the differentiation of energy poverty signatures, and applying them to a spatial energy poverty lens.

PCA results indicate nine energy poverty signatures in North Carolina. Two energy poverty signatures, socio-economic vulnerabilities, and older households using non-electric heat were scale-agnostic or present at every scale. Two signatures were semi-scale agnostic and were present in two of three scales analyzed. The final five signatures were estimated as scale-dependent, occurring at a single scale only. The presence of scale agnostic signatures indicates that even with a change in geographic scale, scale agnostic signatures still explained much of the variation at every scale. The presence of scale-specific signatures however also suggests that using a single scale of analysis will hide energy poverty signatures in analysis aimed to identify energy poverty signatures. This result explicitly shows energy poverty signatures can be dependent on a scale, thus becoming a spatial energy justice issue. Geography can drive the recognition of specific signatures and hide others. Further, while scale agnostic signatures represent signatures that are predominant at all scales, contrasting the vulnerabilities in each scale agnostic and scale specific signature shows that some types of vulnerabilities are not represented in scale specific signatures. Three of five scale-specific signatures contain race-related vulnerabilities while the scale-agnostic signatures contain none. This can mean a lack of recognition of race-related energy poverty signatures and reinforces the issue of single-scale analysis as a spatial energy justice concern.

The signature socio-economic status explained the most variation within the PCA for all three scales. The socio-economic status signature collects three common attributes that are often associated with socio-economic vulnerability, low education attainment, poverty, and disability. This variable pattern supports previous results in a non-US context, as Mashhoodi et al. (Mashhoodi et al., 2019) found income to be spatially homogeneous across the Netherlands. Combined, these socio-economic vulnerabilities are often termed "poverty traps" where income is lowered and expenses are increased, leading to "self-reinforcing mechanisms that maintain poverty" (Haider et al., 2018, p. 311). In energy poverty, these mechanisms often play out as the concept "heat or eat", a serious energy justice issue, where lack of resources means a household cannot effectively afford medical necessities, food, and regulated temperature concurrently (Frank et al., 2006).

Older households using non-electric heat are identified in North Carolina as specific concerns due to a mix of off-grid heat and poor construction. North Carolina residents purchased the fifth most electricity at a residential level of the 50 US states (EIA, 2015). However, fuel oil, liquid propane (LP), and utility (natural) gas are common fuels in homes without electric heat. For example, recognition of LP as a heating fuel is important due to cost and regulation in NC (Harrison & Popke, 2011). LP is closely tied to market value costs of crude oil and its price is not regulated. Lack of regulation can lead to drastic changes in affordability over the year. Older houses tend to be inefficient houses (Harrison & Popke, 2011; Howard et al., 2012; Mashhoodi et al., 2019). Inefficiency coupled with pricing variability and lack of regulation means leads to a unique intersection that is an important energy poverty signature for policy implementation. Contrast this signature to, for example, newer mobile homes, which are also inefficient and often connected to electric heating.

Indicated in Figure 3.2, Scale-specific signatures include African American renters, older populations using fuel heat, older homes using LP heat, African American and American Indian populations using LP heat, and African American populations only using LP heat. This suggests that while many experiences of energy poverty may be similar across socio-economic groups or specific types of infrastructure, specific signatures are missed. This supports the case for using analyses, if possible, that identify signatures and not individual vulnerabilities. African American renters, a scale-specific signature, is mostly a different experience than African Americans using only LP heat and thus requiring different types of interventions. Misrecognition in this form is another energy justice concern that is highlighted by multi-scale vulnerability analysis.

Further, this is explicitly a spatial energy justice concern. Identification of energy poverty signatures with a global analysis such as PCA inherently means that each signature has a specific spatial pattern. In this case, interventions addressing communities and infrastructure must be geographically appropriate and sensitive to the specific issues of each energy poverty signature to account for spatial energy injustices from misrecognition. Misrecognition is also a spatial energy injustice for scale-agnostic signatures. The scale issue of aggregation can be applied to multiple scales of mapping for signatures, where fine-scale information is not the same as aggregated information representing the same area. This is particularly true for the spatial patterns of the socio-economic signature in the urban areas of Raleigh and Charlotte as an example, indicated in Figure 3.3. The signature is still present in census tracts in Figure 3.3D and Figure 3.3E, as indicated by the dark red, but is not detected at the county or CAA level for the same area in Figure 3.3A and Figure 3.3B, as indicated by the dark blue. While areas of socio-economic distress may be prevalent throughout large parts of the state, areas of high population density may hide this signature when aggregated. This phenomenon of aggregation is consistent with previous findings indicating local level patterns in pollution, for example, not present in larger-scale data analysis (Fisher et al. 2006), indicating an injustice through misrecognition.

The use of GWPCA uses geography as an explicit variable in identifying energy poverty signatures. Using spatiality as a variable creates geographic-dependent signatures that can then be used to understand how local identification of energy poverty signatures may be different. In terms of spatial justice concerns, this method addresses the difference in a local v. global methodology. Global methods overweight globally relevant variables and map them to local areas, which may underrepresent or hide highly localized patterns of energy poverty signatures. Local methods, such as GWPCA, build an energy poverty profile based on local strength in data to account for this. In a practical sense, a GWPCA using the regional influence of energy poverty experiences will play a role in determining the energy poverty signatures that might be present, instead of the assumption that all energy poverty vulnerabilities are important in all areas of North Carolina. The GWPCA for this study results suggests that a global PCA may be a limited method to identify energy poverty signatures throughout North Carolina due to inconsistencies between the energy poverty signatures identified with a global and the locally specific GWPCA.

For example, fuel type was a common top-loading variable, indicating that the most variation in these areas was explained by access to energy types. This inconsistency suggests that while a global analysis can identify areas of energy poverty signatures, the importance of that signature is not aligned with the local patterns of energy poverty. It is important to note that when a GWPCA output shows top-loading variables, they could be positive or negatively loaded (Robinson et al. 2019). This indicates some areas might deem an absence of something as important, such as a deficit of heating fuels in specific areas. The absence is consistent with Robinson et. al (2019) findings with a GWPCA of energy poverty vulnerabilities, where many overlaps occur between a global PCA and GWPCA, but geographically do not conform to the global PCA or are statistically more important than are indicated by a global PCA.

GWPCA patterns highlight two major spatial energy justice concerns. First, the GWPCA indicates that energy poverty is a locally specific phenomenon in NC, at both scales. This is evident in both the kernel number reduction in both analyses, indicating a global data set does not capture spatial variability for each scale and a change in dominant vulnerabilities across the study area. A GWPCA can highlight how location changes these components by comparing them to the first component of the global PCA. For example, in the county GWPCA, many top-loading variables are associated with the socio-economic energy poverty signature. However, electric heat is not, indicating that while it is not the most important variable overall, locally it becomes perhaps the most important indicator of the most important energy poverty signature in that area. The same is true for through census tract scale, where renters and electric heat for example are prominent in the GWPCA as top-loading variables but not in the global tract PCA. This provides some backing for the lack of geography as a justice concern. By simply including the use of space as a driver of energy poverty, different forms of energy poverty signatures are recognized in the identification process. The absence of geography means missing locally specific signatures. While some of these signatures and variables would be recognized in other less important signatures in the global analysis, they do provide a way to prioritize locally important signatures. Second, comparing scales of GWPCA analyses indicate that even with the addition of a locally specific parameter, changes in scale will alter what energy poverty signatures are identified. Similar to a global PCA analysis, this is important as patterns are not effectively identified at different scales.

Although results highlight energy poverty signatures consistent with previous findings, the work is subject to common methodological limitations. Selection bias may occur due to the intricacy of socio-economic research. Data was selected through a review of the literature and specific data that has been used to spatially identify energy poverty. Limiting the number of variables selected enhances the interpretability of the results without reducing the efficacy of the study. Further, it is important to note that ACS data was selected as a major component of energy poverty as it is freely available and is commonly used in these analyses. However, ACS is still an aggregated data set and consistently misrepresents underrepresented groups (O'Hare, 2019). The aggregation effect on analysis in this paper may also occur when household data is sampled and aggregated for the ACS. However, it is still valuable to understand broad trends of energy use when making policy decisions or interventions due to the lack of high-quality data.

Policy

The methods above provide a reasonable pathway to improve the just implementation of WAP within two major components. The first through targeted allocation of WAP funds to CAAs, and the second through specifying application requirements for individuals applying for WAP funds.

Allocation

In North Carolina, WAP funds are allocated to CAAs to be distributed at their discretion. WAP allocation amount to individual CAAs is a function of poverty percentage and a CAA's previous year's WAP use efficiency. The methods presented in the paper can redefine allocation based on the local needs of each CAA efficiently, so they address the greatest need locally. First, as CAAs are the common allocation geography through which WAP money is distributed, signatures of energy poverty within each CAA can direct how money can be allocated. For example, areas of more structural vulnerabilities such as mobile homes might be more efficient with an increase in WAP money. Further, mapping the GWPCA and PCA outputs provide an understanding of hidden energy poverty signatures based on scale. Outcomes of the results point to specific areas in the CAA that contain signatures that are not represented at the CAA level. To address all signatures, money can be allocated to CAAs based on CAA level signatures, and then the remainder allocated by CAA to localities or utilities at a smaller level to manage more specific local signatures (such as a few census tracts) there are for efficient interventions. The use of a multi-scalar approach allows the CAAs to flexible allocate money to localities and contractors in locations as they see fit.

Funding Requirements

There is little information required for WAP applications for individuals, with only household income and homeownership the essential screening requirements. Requirements for WAP applications are determined statewide and applied to local areas. This is a procedural spatial justice issue. Implementation of the policy is based on requirements from a large-scale political entity, as opposed to a locally specific one. Allowing for specific WAP requirements based on locality opens the possibility for a just approach to intervening based on requirements not covered by the income/housing tenure requirement.

Using the PCA/GWPCA methods covered in this paper would provide locally specific requirements. First, energy signature outcomes will highlight areas where older homes (a proxy for homes possibly needing weatherization) are associated with energy poverty signatures (or other specified characteristics). For example, Signature 2 in the analysis shows older homes associated with non-electric heating fuels at all scales. Applications could then be open to all associated vulnerabilities so that eligible households would be able to receive weatherization within the areas that are deemed important by local signatures. Ideally, this would include a set of vulnerability characteristics that would be part of the preferences. For example, an income limit may be given with preferences to people with older houses or not on electric fuel. This directly impacts areas that have an increased number of eligible homes but perhaps not a high relative count of houses at 200% poverty status. Next, using the GWPCA outputs to understand the local specifics of the area would narrow down areas of specific importance to alter application procedures. Matching energy poverty policy between scales helps accomplish a scale harmonization that can effectively bring together both statewide and local concerns in a just way.

Another important factor is the procedure through which applications occur. Residents must initiate the application, CAAs do not typically go door to door offering services. Therefore, applications would be self-selecting for people who have access to the internet, or the ability to drive to an office for example. Spatial analysis helps highlight these areas, coinciding with other data such as internet access, that people are not able to even process applications. Further, it helps highlight areas where CAA (or other smaller entity) outreach may be appropriate. For example, only building owners may apply for WAP. Areas where energy poverty signatures indicate housing tenure as a major characteristic of vulnerability in the areas would benefit from reaching out to landlords or developing programs to incorporate landlord-resident-WAP relationships where weatherization can be increased in rental homes. Other examples of this may include fuel types of housing types such as mobile homes, where specific weatherization characteristics may be addressed more efficiently through targeted approaches with utilities than a blanket application system.

Conclusion

US policy does not address energy poverty efficiently, nor are there enough resources to support existing programs in the US (Bednar & Reames, 2020). However, federal programs are increasing funding for energy poverty programs such as WAP, and particular attention needs to be paid to the justice implications of identification and intervention of energy poverty. This work highlights the need for multi-scalar, multi-vulnerability approaches that address as many forms of energy poverty as possible. Spatial energy justice combines the need to attend to both geography and the condition of energy systems and structures at once, as they are intertwined in their production of energy poverty. Specifically, the use of a PCA and energy poverty signatures highlights energy poverty changes based on geographic location and scale. Further, analyzing energy poverty with multiple variables at a singular scale may not sufficiently highlight the multiple and specific experiences that may be occurring. Consistent with the findings of (Mashhoodi et al., 2019; Robinson et al., 2019), different methods may be appropriate at different scales and geographic locations but might be necessary at the same time. Moving forward practitioners and researchers must be aware of the limitations of the single-scale analysis and incorporate a suite of techniques that allows for effective policy, addressing the appropriate processes at appropriate scales (Calderón-Contreras & Quiroz-Rosas, 2017; Mashhoodi et al., 2019), with the often-limited resources available. Recommendations made to the WAP program are a way to provide spatial analysis and energy poverty practitioners with a simplified tool to distinguish needs based on spatial energy justice principles. Policy flexibility in both target and geography will fill the drive toward local, community-based solutions that target energy poverty in more just ways.

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Supplementary Information

Table 3.2

Descriptive statistics of 18 selected energy poverty vulnerabilities for North Carolina census tracts

	Census Tract					
	Count					
Variable	Mean	Median	Min	Max	SD	Obs
households	1,785.24	1704	0	7,004	806.05	2,195
housing units	2,083.40	1989	0	8,096	916.86	2,195
total population	4,626.71	4386	0	18,242	2,141.10	2,195
age over 66	502.91	472	0	2,333	266.61	2,195
disability	471.49	439	0	2,339	255.01	2,195
SNAP benefits	234.89	197	0	1,254	184.53	2,195
house built before 1970	805.06	769	0	2,767	480.44	2,195
mobile home	271.28	133	0	3,084	324.66	2,195
electric heating fuel	1,123.12	1019	0	6,724	651.10	2,195
fuel oil heating fuel	56.57	20	0	811	91.02	2,195
LP gas heating fuel	126.11	62	0	986	156.62	2,195
renter	624.10	514	0	4,306	467.47	2,195
utility gas heating fuel	435.96	283	0	3,561	471.54	2,195
African American population	992.99	638	0	11,144	1,060.34	2,195
American Indian population	55.29	6	0	6,547	296.26	2,195
Hispanic population	426.40	278	0	4,418	470.98	2,195
high school or below education	396.29	349	0	2,075	283.71	2,195
poverty	489.16	419	0	3,927	356.35	2,195
	Ratio					
Variable	Mean	Median	Min	Max	SD	Obs
age over 66	0.29	0.29	0.00	1.00	0.10	2,164
disability	0.27	0.27	0.00	0.53	0.10	2,164
SNAP benefits	0.14	0.12	0.00	0.73	0.11	2,164
house built before 1970	0.42	0.41	0.00	1.00	0.22	2,166
mobile home	0.13	0.07	0.00	1.00	0.14	2,166
electric heating fuel	0.62	0.64	0.10	1.00	0.18	2,164
fuel oil heating fuel	0.03	0.01	0.00	0.42	0.05	2,164
LP gas heating fuel	0.07	0.04	0.00	0.50	0.08	2,164
renter	0.36	0.31	0.00	1.00	0.20	2,164
utility gas heating fuel	0.25	0.19	0.00	0.89	0.23	2,164
African American population	0.22	0.15	0.00	0.97	0.21	2,171
American Indian population	0.01	0.00	0.00	0.89	0.06	2,171
Hispanic population	0.09	0.06	0.00	0.70	0.08	2,171
high school or below education	0.09	0.08	0.00	0.32	0.06	2,171
poverty	0.11	0.10	0.00	0.60	0.07	2,171

Table 3.3

Descriptive statistics of 18 selected energy poverty vulnerabilities for North Carolina counties

	County					
	Count					
Variable	Mean	Median	Min	Max	SD	Obs
households	39,185.97	21,243.50	1,631	403,546	61,252.31	100
housing units	45,730.66	26,090.00	2,229	435,795	66,318.80	100
total population	101,556.24	55,205.00	4,119	1,054,314	161,428.12	100
age over 66	11,038.93	7,104.00	566	78,927	13,070.25	100
disability	10,349.31	6,940.50	478	67,998	11,371.42	100
SNAP benefits	5,155.77	3,528.00	314	40,063	6,057.34	100
house built before 1970	17,670.99	11,326.00	1,274	133,212	21,194.53	100
mobile home	5,954.68	4,988.00	546	20,342	4,057.25	100
electric heating fuel	24,652.38	14,125.00	685	207,229	33,244.50	100
fuel oil heating fuel	1,241.82	652.50	67	10,991	1,613.93	100
LP gas heating fuel	2,768.14	2,396.50	415	12,662	1,874.89	100
renter	13,698.92	6,407.50	460	175,647	25,067.88	100
utility gas heating fuel	9,569.31	1,434.50	31	200,091	27,779.63	100
African American population	21,796.22	10,952.50	13	330,161	45,144.66	100
American Indian population	1,213.52	320.00	6	52,630	5,295.15	100
Hispanic population	9,359.50	3,216.50	41	137,405	18,732.92	100
high school or below education	8,698.66	6,012.00	709	69,881	9,940.85	100
poverty	10,737.17	6,499.50	644	90,365	13,813.29	100
	Ratio					
Variable	Mean	Median	Min	Max	SD	Obs
age over 66	0.33	0.34	0.18	0.46	0.06	100
disability	0.32	0.32	0.16	0.46	0.06	100
SNAP benefits	0.16	0.15	0.06	0.29	0.06	100
house built before 1970	0.43	0.44	0.17	0.64	0.10	100
mobile home	0.20	0.20	0.01	0.38	0.08	100
electric heating fuel	0.65	0.65	0.29	0.93	0.12	100
fuel oil heating fuel	0.06	0.03	0.00	0.33	0.07	100
LP gas heating fuel	0.13	0.12	0.01	0.50	0.08	100
renter	0.30	0.29	0.16	0.49	0.07	100
utility gas heating fuel	0.12	0.07	0.01	0.50	0.12	100
African American population	0.20	0.18	0.00	0.61	0.16	100
American Indian population	0.02	0.00	0.00	0.39	0.05	100
Hispanic population	0.07	0.06	0.00	0.22	0.04	100
high school or below education	0.11	0.11	0.05	0.20	0.03	100
poverty	0.12	0.12	0.06	0.22	0.03	100

Table 3.4

Descriptive statistics of 18 selected energy poverty vulnerabilities for North Carolina Community Action Agencies

	Community Action Agency					
	Count					
Variable	Mean	Median	Min	Max	SD	Obs
households	118,745.36	79,734	15,699	403,546	92,777.79	33
housing units	138,577.76	103,117	25,557	435,795	99,631.55	33
total population	307,746.18	209,644	34,410	1,054,314	245,073.36	33
age over 66	33,451.30	27,950	6,851	78,927	20,133.54	33
disability	31,361.55	26,251	4,928	67,998	17,767.46	33
SNAP benefits	15,623.55	12,227	1,794	40,063	9,732.56	33
house built before 1970	53,548.45	40,493	10,905	133,212	31,190.07	33
mobile home	18,044.48	15,000	3,507	69,205	12,370.73	33
electric heating fuel	74,704.18	56,897	8,841	207,229	52,169.02	33
fuel oil heating fuel	3,763.09	2,685	359	18,565	3,726.01	33
LP gas heating fuel	8,388.30	6,878	1,797	23,126	4,803.00	33
renter	41,511.88	22,391	4,277	175,647	38,607.13	33
utility gas heating fuel	28,997.91	11,187	462	200,091	45,176.05	33
African American population	66,049.15	39,101	489	330,161	71,592.04	33
American Indian population	3,677.33	1,165	193	65,039	11,113.37	33
Hispanic population	28,362.12	15,680	2,046	137,405	30,103.33	33
high school or below education	26,359.58	22,447	2,938	69,881	15,547.66	33
poverty	32,536.88	22,141	3,970	90,365	21,614.27	33
	Ratio					
Variable	Mean	Median	Min	Max	SD	Obs
age over 66	0.31	0.31	0.20	0.44	0.06	33
disability	0.29	0.31	0.16	0.38	0.05	33
SNAP benefits	0.14	0.14	0.06	0.25	0.04	33
house built before 1970	0.41	0.42	0.23	0.54	0.08	33
mobile home	0.16	0.17	0.01	0.28	0.07	33
electric heating fuel	0.64	0.62	0.44	0.89	0.11	33
fuel oil heating fuel	0.05	0.03	0.00	0.22	0.05	33
LP gas heating fuel	0.10	0.07	0.01	0.25	0.06	33
renter	0.32	0.31	0.19	0.46	0.06	33
utility gas heating fuel	0.18	0.13	0.02	0.50	0.14	33
African American population	0.19	0.18	0.01	0.54	0.13	33
American Indian population	0.01	0.00	0.00	0.13	0.03	33
Hispanic population	0.08	0.07	0.03	0.14	0.03	33
high school or below education	0.10	0.09	0.05	0.15	0.02	33
poverty	0.11	0.11	0.06	0.17	0.03	33

Table 3.5

PCA Loadings for 3 scales and 4 components

	CAA			
Variable	PC1	PC2	PC3	PC4
pop_hs	0.32			
hh_dis	0.36			
hh_snap		-0.43		
pop_pov	0.28			
hu_mob	0.34			
hh_66	0.34			
ohu_lpgas	0.28			-0.40
ohu_fo		0.34	-0.32	
pop_ai			0.43	-0.47
hu_1970			-0.54	
ohu_elec		-0.27	0.45	0.57
ohu_rent		-0.41		
pop_aa		-0.53		-0.32
pop_his	-0.28			
ohu_ugas	-0.31		-0.25	
	County			
Variable	PC1	PC2	PC3	PC4
pop_hs	0.37			
hh_dis	0.38			
hh_snap	0.34	0.33		
pop_pov	0.30			
hu_mob	0.36		0.27	
hh_66	0.26	-0.33		-0.26
ohu_lpgas	0.32			-0.29
ohu_fo		-0.34	-0.39	0.32
pop_ai				0.67
hu_1970	0.28		-0.36	
ohu_elec			0.67	
ohu_rent		0.47		
pop_aa		0.46		-0.37
pop_his		0.25		
ohu_ugas	-0.26	0.26	-0.34	
	Tract			
Variable	PC1	PC2	PC3	PC4
pop_hs	0.40			
hh_dis	0.39			
hh_snap	0.37	-0.27		
pop_pov	0.33	-0.27		
hu_mob	0.36	0.29		
hh_66		0.32	-0.34	
ohu_lpgas		0.30		
ohu_fo			-0.32	-0.39
pop_ai				0.71
hu_1970			-0.39	
ohu_elec			0.66	-0.27
ohu_rent		-0.44		
pop_aa		-0.39		
pop_his		-0.26		
ohu_ugas	-0.36	-0.28	-0.37	

CHAPTER 4: MUTLI-SCALE SPATIAL ANALYSIS OF ESTIMATED ENERGY USE INTENSITY AND SOCIOECONOMIC INDICATORS OF ENERGY POVERTY

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Abstract

Energy poverty is the inability to access energy as needed. Energy poverty is a multidimensional societal concern, especially for health. Recently, the spatial energy patterns of energy poverty have become a focus of researchers to identify how geography affects the outcome of energy poverty experiences. While identifying the locations of energy poverty patterns is vital, there is some focus on the justice aspects of location, namely the unequal experiences of energy poverty due to the multiple entangled spatial relationships of the drivers and indicators of energy poverty. Geographic scale is an equity concern due to aggregating and disaggregating data for ease of use, with the possibility of misidentifying both the patterns of energy poverty and the scales at which the patterns occur. Misidentification of the scale of these patterns can lead to inappropriate policy addressing these issues. In this paper, I explore the scalar relationship between energy use intensity, a proxy for energy poverty, and socioeconomic characteristics. First, a county-level EUI estimation was performed for nine states in the Eastern US. Next the relationship between socio-economic characteristics and estimated EUI was explored through an OLS regression and two spatial models, a Geographically Weighted Regression (GWR) and a Multiscale Geographically Weighted Regression (MGWR). Results of the models show a distinct spatial relationship between EUI and socioeconomic indicators of energy poverty, where EUI is predicted more effectively on a local level. MGWR results indicate that the multiple socio-economic characteristics also vary in geographical scale with their relationship to the EU, with some having a global influence while others are highly localized. These results show a need for careful consideration for scale for effective policy interventions for energy poverty.

Keywords: GIS, Energy Poverty, Energy Use Intensity, Geographically Weighted Regression (GWR), Multiscale Geographically Weighted Regression

Introduction

Energy poverty is the inability to access energy as needed for a comfortable life. Energy poverty has gained traction in the academic and professional world over the last 30 years as a serious societal issue that must be addressed (Bouzarovski & Petrova, 2015; Herrero, 2017). To confront energy poverty, the identification of both its causes and locational patterns is vital (Herrero, 2017). Policy and practitioners have developed benchmarks, such as income thresholds, to understand who is burdened by the cost of energy (Boardman, 1991). In-home decisions, such as necessary spending (Frank et al., 2006), or housing quality (Hernández et al., 2016) are also used to identify possible energy poverty experiences. However, the causes of energy poverty are hard to define outright, due to its multifaceted connections with policy (Bednar & Reames, 2020; Gupta & Gregg, 2020), geography (Bouzarovski & Simcock, 2017), energy infrastructure (Harrison, 2013), and more. Each one of these factors is contextual to the other, where a single household's experience with energy poverty is not the same as the next. This variation is often at odds with the need for efficient interventions through policy, either community or broader, where one-size-fits-all interventions dominate.

While it is well understood that there is a relationship between geography and energy poverty experiences, quantitative spatial analysis of energy poverty is still a growing part of the energy poverty field (Bouzarovski & Simcock, 2017). Further, though location and space are identified as drivers of the experience of energy poverty, there has been little exploration into the spatial energy justice impacts of spatial analysis of energy poverty. Spatial energy justice is what we term the combination of energy poverty and spatial justice. Energy justice is a framing that calls for equity in the benefits and burdens of energy poverty. The frame is set into three specific components, distributive, procedural, and recognition (Hernández, 2015). Distributive justice is concerned with equal distribution geographically of energy poverty, procedural justice with equality in policy actions, and recognition with equity in the determination of who is experiencing energy poverty. Spatial Justice is a term first characterized by Soja (2010) based on work by Harvey (1973, 1996) and Young (1990), that highlights the considerations of social and physical processes in space on social justice outcomes. The main determination of species geography as both a "container" for outcomes and a lens through which these social processes occur. Combined these are what we term *spatial energy poverty* or the intersection of geography driving justice within energy poverty. A current example of spatial energy justice concern has been brought to the forefront due to the COVID-19 crisis. During the first year of the COVID crisis, many US States instated moratoriums on utility disconnections, preventing utilities from stopping power and water services if the resident could not pay. However, both the extent and length of these laws varied widely by state, leading to vastly different experiences where power may be shut off, in a pandemic, solely dependent on where you live (Flaherty et al., 2020). This is a direct example of location driving the residents' access to energy poverty, a spatial energy justice issue. Both procedural and distributional justice concerns intertwine to create unequal outcomes.

A major factor of spatial energy justice is scale (Bouzarovski & Simcock, 2017). Scale is an often contested and confusing term in the field of geography and can have multiple meanings simultaneously (Castree et al., 2009). This study incorporates the definition of scale as a literal geographic extent of a phenomenon, particularly in the discussion of the methodology of spatial models. As a bound for statistical analysis, the choice of scale can alter the outcomes of analyses. An example of this is data aggregation. Energy is consumed in the household, but the analyses of energy consumption (and the outcomes of that consumption) are often performed at a larger geographic area. However, data at a geographic scale other than the household can obscure energy poverty experiences (Robinson et al., 2018) where individual experiences or outcomes may be missed, as the large areas do not collectively reflect the same characteristics of all individual households contained within. Recognizing energy poverty characteristics at an appropriate scale, particularly if at multiple scales, is important for just interventions.

To enact just policy, it is important to not only understand where and at what scale energy poverty occurs but what form it takes. A set of research in sociology, public health, and geography has identified socio-vulnerability as a way to measure the likelihood of someone experiencing an environmental burden (Cutter, 1996; Cutter et al., 2003; Schmidtlein et al., 2008). That same concept is used in energy poverty to begin mapping and identifying a household's vulnerability to energy poverty specifically (Middlemiss & Gillard, 2015; Papada & Kaliampakos, 2019; Sanchez-Guevara et al., 2019). Indicators such as type of household, income, race, disability status, children, and others have been linked with the increase in energy poverty, and are often used to identify a vulnerability to energy poverty. However, it is difficult to quantify expansive, shared energy poverty through means other than survey data. Survey data is a prominent vehicle for analysis in energy poverty research but is hard to scale to large populations (Morris & Genovese, 2018; Mould & Baker, 2017). Further, accessing energy use data on a large scale is difficult due to regulations around utility-owned data in the US (Bednar & Reames, 2020).

Sampled survey microdata is one way to estimate energy use geographically without access to data. In the US, recent work has begun exploring using the Energy Information Associations (EIA), Residential Energy Consumption Survey (RECS) data to estimate energy use for small scale areas, effectively using sampled data to estimate energy use by matching it to higher resolution data (Min et al., 2010; Reames, 2016). RECS collects energy use and demographic data for a set of sampled households when conducted. The last RECS data to be released was in 2015 (EIA, 2015), and the microdata contains around 5,600 sampled homes to represent 118 million American homes in total. While RECS data is broad geographically, preventing samples to be used alone to estimate energy use at a small scale, Min et al. (2010) developed a method to downscale energy use coupled with demographic data to smaller geographies. Other data products use other representative sample data at smaller and larger geographic sales to provide these estimations, including regional energy non-profits and some utilities (Buylova, 2020). Downscaling estimated energy use facilitates spatial analysis due to the high resolution and ubiquity of the data which is difficult to accomplish without access to large amounts of utility data in the first place.

An advantage of acquiring accurate energy consumption data in the home is to measure the efficiency of energy use concerning the residential characteristics of the area. One of the most common metrics to identify poor energy efficiency is through house footprint measurement called Energy Use Intensity (EUI) (Bednar et al., 2017; Reames, 2016; Tong et al., 2021), a measure of energy use for the size of a dwelling. It is generally understood that an increase in EUI is a decrease in home efficiency (Reames, 2016). Although EUI is not a comprehensive indicator of energy poverty, it does provide a benchmark of energy burden or the use of a disproportionate amount of energy compared to income (Drehobl & Ross, 2016). High EUI is commonly found in low-income households where overall energy use is low, but the amount spent relative to income on energy is extremely high (Tong et al., 2021). Therefore, EUI is often used as a proxy for the burden energy use places on a household's income, where a high EUI indicates a high percentage of income to energy. To understand the relationship of EUI to socioeconomic characteristics over a geographic area, energy use can be matched to the appropriate geography. Min et al. (2010), developed a methodology to scale energy use from RECS to zip codes in the US, by using the relationship of energy use to home characteristics in the RECS data and applying that model to zip codes through matching census data. The downscaling methodology was refined by Reames (2016) to include EUI, and the resulting EUI was used to compare with socioeconomic characteristics in Kansas City. The approach highlighted the importance of the spatial relationship of EUI to socioeconomic characteristics, showing that high EUI areas were associated with a variety of socioeconomic vulnerabilities. In this case, the relationship can be understood as a proxy for understanding the likelihood of a house in the area experiencing energy poverty.

This study focused on understanding the spatial justice implications of scale driving the relationship between EUI and socioeconomic characteristics. The estimated EUI methodology provided a downscaled product that is used in a set of spatial analyses to measure the relationships between socioeconomic indicators and energy use. These include a geographically weighted regression (GWR) (S. Fotheringham et al., 1998) and multiscale geographically weighted regression (MGWR (Stewart Fotheringham et al., 2017). A GWR is similar to an ordinary least squares (OLS) regression, except the regression is performed at every observation using a nearest-neighbors bandwidth. An MGWR is also similar, except that while also allowing for spatial change, it also does not assume the scale of the relationship is the same for every variable. Both a GWR and MGWR provide an understanding of the spatial patterns of the relationship between the variables and do not assume that the relationship is the same across the entire study area. An MGWR decouples the bandwidth of the nearest neighbors kernel for every variable, whereas the GWR assumes it is the same for every variable. The use of these models improved on the previous studies by including assumptions of spatial energy poverty, in particular, that vulnerabilities to energy poverty collocate (Meyer et al., 2018), are spatial (Bouzarovski & Simcock, 2017), and are multi-scalar (Morrison & Shortt, 2008). The outcomes of this work provided an estimated EUI model for the Eastern US, coupled with a better understanding of the spatial justice implication of scale on policy outcomes.

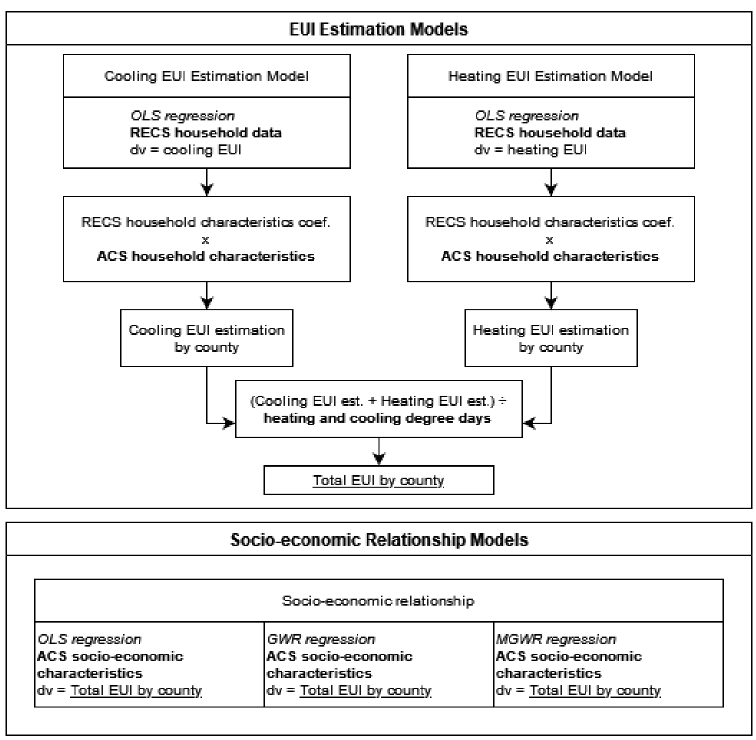
Methods

To estimate EUI and explore the spatial relationship of EUI to socioeconomic characteristics, three models were used. An energy use intensity (EUI) estimation model was developed using weighted sample data to approximate energy use per square foot for cooling and heating across 588 counties in the Eastern US. The EUI estimation methodology is based on Min et al. (2010), Reames (2016), and Buylova (2020), with the following modifications. HDD and CDD terms were added to accommodate the wide range of climates within the region. Then data were harmonized with the county as the geographic downscaling and not the census tract or block. Finally, a model was performed for heating and cooling and summed for total energy use by county. Last, Reames (2016), estimated EUI through 2008 RECS data which reported some sampled data on the State scale and not the EIA Region scale, leading to more geographic variation within the sampled data used for the area. Using the EUI outputs as the dependent variable, a model was fit using socioeconomic variables related to vulnerability to energy poverty to understand the relationship between the intensity of consumption and vulnerability indicators. Finally, two spatially specific models, a Geographically Weighted Regression (GWR) and a Multiscale Geographic Weighted Regression (MGWR) were fit to explore the spatial and scalar relationships between vulnerability indicators and energy use intensity.

Figure 4.1

Data sources and research flow chart for the project. Name column coincides with the names of the variable set used in model methodology.

Data			
Name	Dataset	Variables	Unit
RECS household characteristics	2015 RECS microdata Atlantic South region	heating EUI (kBTU/sq.ft) cooling EUI (kBTU/sq.ft) Year Constructed Housing Type Primary Fuel Heat (heating OLS only) Home Ownership Heating Degree Day (heating OLS only) Cooling Degree Day (cooling OLS only) Household Income Number of Bedrooms	Household (~1000 households)
ACS household characteristics	2015 ACS data	Year Constructed Housing Type Primary Fuel Heat Home Ownership Household Income Number of Bedrooms	County (588 counties)
ACS socio-economic characteristics	2015 ACS data	% age 25 & below high school education % age over 65 % percent African American % Hispanic % in poverty status last 12 months median income % age below 18 % households renter occupied	County (588 counties)
heating & cooling degree days	2015 HDD & CDD	2015 average heating degree day 2015 average cooling degree day	County (588 counties)



EUI Estimation by County

The EUI estimation model introduced previously used household characteristics from the 2015 residential energy consumption survey (RECS). The RECS is a national set of data products released by the US Energy Information Association (EIA) from a survey conducted over a year in 2015 (EIA, 2015). To understand US residential energy trends, it provides broad energy use characteristics including socioeconomic characteristics along with broad geographic indicators and climate data that are used to provide insight into energy use. Along with aggregated data calculated from the survey, a set of microdata is also produced. RECS microdata includes individual responses to the RECS along with representative sample weights for each response. To anonymize households, 2015 RECS microdata was identified geographically by EIA regions. The Atlantic South was used in the EUI estimation model, and includes 9 states: Delaware, Maryland, West Virginia, Virginia, North Carolina, South Carolina, Florida, and Georgia, and contained a total of 1058 responses.

ACS home characteristics matching the RECS home characteristics were used to scale estimated EUI for the Atlantic South region down to the county level. 2015 ACS 5-year data and county spatial extents were downloaded from the r-package tidycenus (Walker & Herman, 2021). Descriptive statistics for the included variables in the EUI estimation regressions are found in the appendix.

To estimate heating and cooling EUI for the Atlantic South region, two OLS models were fitted using (1):

$$\ln E = \beta_0 + \sum_{i}^{n} \beta_i \cdot \chi_{i,RECS} + \varepsilon \tag{1}$$

using E as EUI, for heating and cooling each and XRECS as the RECS predictor variables. The independent variables used for each OLS model were total heating use and total cooling use divided by the area of the home, which resulted in the EUI for each household. Total cooling in the RECS household characteristics data is electricity used for air conditioning (including non-central units), as that is the only fuel type used for cooling in households. Heating in the RECS household characteristics data is the sum of fuel used for heating in the household which includes natural gas, propane, fuel oil, electricity, and wood.

All RECS household characteristics used in the EUI estimation models are categorical, except degree day data. To match, HDD and CDD for each observation were categorized into 1000 degree-day bins, beginning at 0. The dependent variable EUI was log-transformed for each model to better estimate the relationship between EUI and household characteristics (Min et al., 2010). In total, seven RECS household categorical variables were used as part of the heating estimation regression, for a total of 36 categories. For the cooling EUI estimation model, six categorical variables were used (heating fuel estimation was not used to estimate cooling) for a total of 31 categories. All regression coefficients were retained after the regression, even if non-significant, for the proper estimation of the energy use intensity and avoiding bias (Buylova, 2020). A total of 92 responses were removed from the heating EUI estimation model due to no heating reported, or outliers where extreme amounts of energy were being used for a small area. 48 responses were removed from the cooling EUI estimation for no cooling being reported or extreme outliers.

To scale the EUI estimation for the Atlantic Southeast region to individual counties in the region, each coefficient from both EUI estimation models was multiplied by matching ACS household characteristics collected at the county level. To harmonize the two data sets, the ACS household characteristics are set to a ratio to approximate the binary categorical variable from the RECS household characteristics. The ratio is achieved by dividing the number of households in categories from ACS data by the total number of households in the county. Once the coefficient is multiplied by the ACS data, the total sum of the weighted factors is added to estimate the natural log of EUI using (2):

$$\widehat{\ln E} = \widehat{\beta}_0 + \sum_{i}^{n} \widehat{\beta}_i \cdot \chi_{i,CENSUS} + \varepsilon \tag{2}$$

with E as EUI and X_{CENSUS} as the census harmonizing variables. B_i indicates the regression coefficients of the EUI estimation OLS model. Once summed, the total is transformed back to an estimated EUI used through a scaling function shown in (3):

$$\widehat{E} = exp\left(\frac{RMSE^2}{2}\right) \cdot exp\left(\widehat{\ln E}\right) \tag{3}$$

as a simple exponent function to transform back traditionally underestimates energy use. The final EUI estimations by county are expressed as the average energy use of a household in the given county.

Because temperature is one of the strongest drivers of energy use (Min et al., 2010; Sovacool & Mukherjee, 2011), it is difficult to compare overall energy use between climates. Heating often takes up the most energy in residential buildings, and colder climates often see higher EUI because of this. To make a proper comparison concerning EUI and socioeconomic variables, EUI must be normalized for every county. The equation for weather normalization is indicated in (4) and is reported in BTUs per square foot per total degree day.

$$weather\ normalized\ total\ EUI = \frac{EUI_{cooling} + EUI_{heating}}{HDD + CDD} \tag{4}$$

To calculate the regional heating degree days and cooling degree days to weather normalize for each county, 65-degree base HDD and CDD raster data for 2015 were downloaded from USPEST.org (Oregon IPM Center, 2020). HDD and CDD are measures of heating and cooling that capture the amount of time and how far an area is above or below a 65-degree threshold over a given period. The higher the number, the more cooling or heating is needed to meet the 65-degree threshold. These data were in 30x30 meter rasters and the mean HDD and CDD were calculated for each county using Rstats.

Socioeconomic characteristics

Once a weather-normalized total EUI estimation by the county had been calculated, a set of 7 ACS socioeconomic characteristics (Percent African American, Percent poverty status in last 12 months, Percent without a high school education, Median income, Percent population over 65, Percent Hispanic population, Percent with a disability, Percent population under 18, Percent households renter-occupied) were used to examine the relationship between EUI and socioeconomic indicators at a county level. 2015 ACS 5-year data were used for the ACS socioeconomic characteristics and acquired by county using the same process as the ACS household characteristics. Variables percent Hispanic and percent African American were log-transformed for a better response in the model, and all data were normalized before the OLS and all following analysis.

Because both EUI and socioeconomic patterns are commonly identified as geographically dependent, a Moran's I test was performed (Moran, 1950). A Moran's I analysis is commonly used to test for spatial autocorrelation, a process by which observations near to each other influence the outcomes, breaking the basic assumption of an OLS regression that observations are independent of one another.

A geographically weighted regression was performed to account for the spatial dependencies on a local level and to understand the spatial patterns of the independent variables. A GWR calculates a regression at every observation using a set of surrounding observations identified as a goodness-of-fit function. A bandwidth is selected for every model fit and the GWR is iterated until the goodness of fit is maximized. The resulting kernel is the estimated highest significant neighbor with the best model explanatory power for all variables. The GWR used the Akaike information criterion modified for small sample sizes (AICc) goodness-of-fit estimator (Hurvich & Tsai, 1989). The bandwidth estimation and GWR analysis were run using the program MGWR (Oshan et al., 2019).

An MGWR is similar to a GWR except that the kernel bandwidth is calculated independently by variable and not for a complete model. The independent bandwidth calculations allow for an increase in model power and a better understanding of the scale of influence for each variable on the outcome. The MGWR was run with the same terms as the GWR using the program MGWR.

Results

EUI Estimation by County

The heating model showed a strong explanatory power using the set of household characteristics with an R^2 of .68 while the cooling model showed a moderate explanatory power with an R^2 of 0.39. Results of both the heating and cooling EUI estimation models are shown in Table 4.1 and Table 4.2. The variable inflation factor for all variables was below three for all variables consistent with an appropriate level for a regressions model (Menard, 2002). The heating model showed heteroskedasticity which was corrected using robust error terms and is reflected in Table 4.1. The F value for both models indicates the sample sizes are large enough for model significance.

Table 4.1

OLS regression results for estimated heating EUI (a) and estimated cooling EUI (b). Variables in bold indicate significance at 0.1 level.

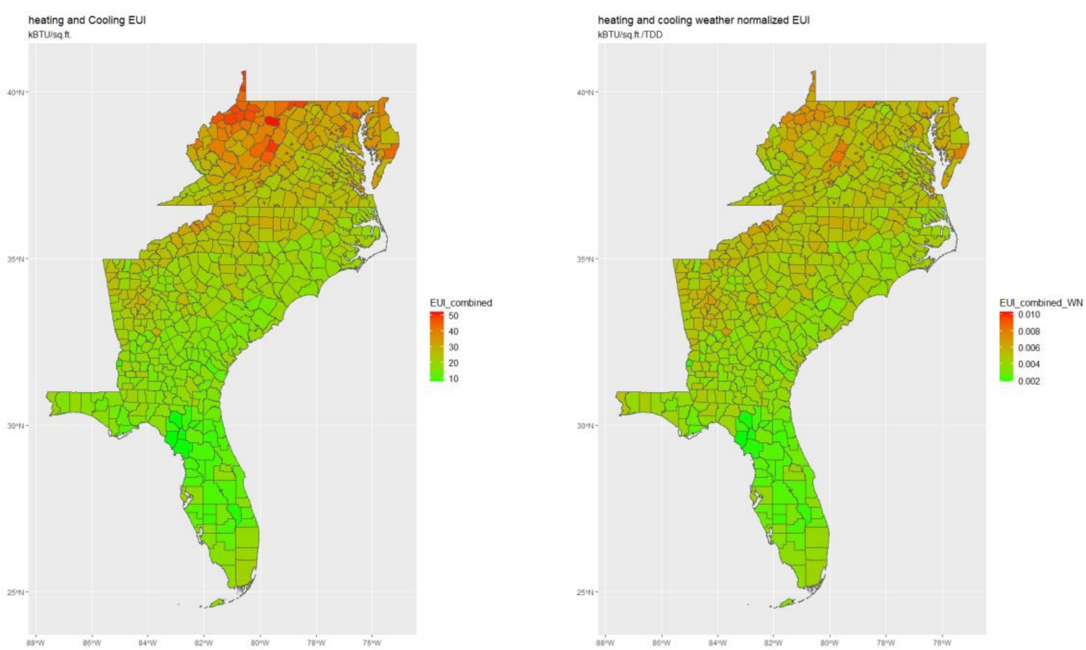
dependant variable =	*ln(BTUSPH_EUI)*	
Predictors	Estimates	p
Year Constructed		
Before 1950	reference	
1950-1959	-0.06	0.729
1960-1969	**-0.33**	**0.065**
1970-1979	-0.17	0.265
1980-1969	**-0.57**	**0.002**
1990-1969	**-0.49**	**0.001**
2000-1969	**-0.48**	**0.002**
2010 to present	**-0.55**	**0.002**
Housing Type		
Mobile Home	reference	
Single Family Attached	**0.73**	**<0.001**
Single Family Detached	**0.48**	**0.007**
Multifamily	**0.96**	**<0.001**
Primary Fuel Heat		
natural gas	reference	
LP Gas	-0.21	0.166
Fuel Oil	0.08	0.461
Electricity	**-0.8**	**<0.001**
Wood	**-1.37**	**0.097**
Home Ownership		
Own	**-0.15**	**0.098**
Heating degree day range		
HDD < 1000	reference	
HDD 1000-1999	**1.6**	**<0.001**
HDD 2000-2999	**1.87**	**<0.001**
HDD 3000-3999	**2.16**	**<0.001**
HDD 4000-4999	**2.27**	**<0.001**
HDD 5000+	**2.33**	**<0.001**
Household Income		
< $20,000	reference	
$20,000 - $39,999	0.07	0.609
$40,000 - $59,999	-0.08	0.512
$60,000 - $99,999	-0.09	0.468
$100,000+	-0.12	0.311
Number of Bedrooms		
0 Bedrooms	reference	
1 Bedroom	-0.28	0.453
2 Bedrooms	-0.2	0.586
3 Bedrooms	-0.11	0.772
4 Bedrooms	-0.19	0.611
5+ Bedrooms	-0.24	0.577
Model Statistics		
(Intercept)	1	0.009
Observations	966	
R2 / R2 adjusted	0.682 / 0.672	
RMSE		
F (29, 936)	69.2	< 2.2e-16

dependant variable =	*ln(BTUCOL_EUI)*	
Predictors	Estimates	p
Year Constructed		
Before 1950	reference	
1950-1959	-0.15	0.146
1960-1969	**-0.39**	**<0.001**
1970-1979	**-0.42**	**<0.001**
1980-1969	**-0.55**	**<0.001**
1990-1969	**-0.65**	**<0.001**
2000-1969	**-0.7**	**<0.001**
2010 to present	**-0.84**	**<0.001**
Housing Type		
Mobile Home	reference	
Single Family Attached	**0.64**	**<0.001**
Single Family Detached	**0.55**	**<0.001**
Multifamily	**0.82**	**<0.001**
-	-	-
-	-	-
-	-	-
-	-	-
-	-	-
Home Ownership		
Own	**-0.14**	**0.02**
Cooing degree day range		
CDD < 1000	reference	
CDD 1000-1999	**0.35**	**0.001**
CDD 2000-2999	**0.79**	**<0.001**
CDD 3000-3999	**1.1**	**<0.001**
CDD 4000-4999	**1.48**	**<0.001**
CDD 5000+	**1.72**	**<0.001**
Household Income		
< $20,000	reference	
$20,000 - $39,999	**-0.2**	**0.004**
$40,000 - $59,999	-0.08	0.254
$60,000 - $99,999	**-0.21**	**0.005**
$100,000+	**-0.2**	**0.011**
Number of Bedrooms		
0 Bedrooms	reference	
1 Bedroom	0.13	0.457
2 Bedrooms	-0.26	0.124
3 Bedrooms	-0.2	0.257
4 Bedrooms	-0.29	0.108
5+ Bedrooms	-0.25	0.218
Model Statistics		
(Intercept)	1.41	<0.001
Observations	1010	
R2 / R2 adjusted	0.398 / 0.383	
RMSE		
F (25, 984)	26.07	< 2.2e-16

Estimation of total EUI by county for both heating and cooling was completed using coefficients from Table 4.1 and Table 4.2, multiplied by the matching ACS household characteristic data by county. A scaling equation (3) was used to transform both outputs back to total EUI by county. Once both cooling and heating were transformed, they were summed at every county, resulting in total EUI by county, shown in Figure 4.2. While it is difficult to verify energy use intensity for a given area, the range of EUI values is consistent with reported EIA averages for the region as well as differences between climatic and regional averages reported by the EIA in 2015 (EIA, 2015). The range of total estimated EUI ranges from the EUI estimation model is 20 to 80 kilo British thermal unit (kBTUs). The EIA reports EUI to similar ranges, with colder climates having higher EUI than warmer climates.

Figure 4.2

Estimation of combined heating and cooling EUI (left) and weather-normalized combined heating and cooling EUI (right). Red indicates a higher EUI.



Socioeconomic Models

To understand the relationship between socioeconomic indicators to energy poverty and EUI, a regression model for the study area fit, using a weather-normalized total EUI by county as the dependent variable and ACS socioeconomic characteristics as the independent variables. The final model outputs are shown in Table 4.2. The variable inflation factor (VIF), a measure of multicollinearity in a multivariate model, was below three for all variables indicating none needed to be dropped. This is an acceptable threshold for multicollinearity measured with VIF (Buylova, 2020).

Table 4.2

Socioeconomic indicators OLS regression results

dependant variable =	*(EUI_combined)*	
Predictors	Estimates	p
% Age 25 + below HS education	-0.143	0.011
% Age 65+	-0.162	0.001
% African American	-0.142	0.001
% Hispanic	-0.294	0
% Poverty status last 12 months	0.079	0.223
% with disability	-0.143	0.001
median income	0.124	0.089
% below age 18	-0.135	0.006
% renter occupied	0.061	0.148
Model Statistics		
(Intercept)	0	1
Observations	588	
R2 / R2 adjusted	0.195 / 0.182	
RMSE		
F (9, 578)	15.51	< 2.2e-16

Table 4.3

Comparison of the goodness of fit scores reported for three socioeconomic models. Lower AICc indicates better model fit.

	Model		
	OLS	GWR	MGWR
AICc	1563.949	1011.524	917.744
Adj. R2	0.182	0.751	0.779

A Moran's I analysis was run using the parameters of the fit socioeconomic indicators model to test for autocorrelation. The Moran's I coefficient was 17.5 and was significant at a 0.001 level indicating that spatial clustering of values is not the result of random spatial processes and that spatial-autocorrelation was present.

To account for spatial dependency and to illustrate the spatial relationship of ACS socioeconomic characteristics to total EUI by county a geographically weighted regression was fit. The AICc, a factor measuring the explanatory power of each model, was lower for the GWR indicating a better model fit for the data, show in Table 4.3. The optimum bandwidth was 108 neighbors for the GWR model and was used for the final model fit.

A multi-scalar geographically weighted regression was run next due to the assumption that relationships between each socioeconomic characteristic and total EUI do not act on the same scale. The results show an improvement over the GWR, with an AICc of 917, indicating it had the strongest explanatory power of the three models run. The individual bandwidths for each socioeconomic characteristic are shown in Table 4.4.

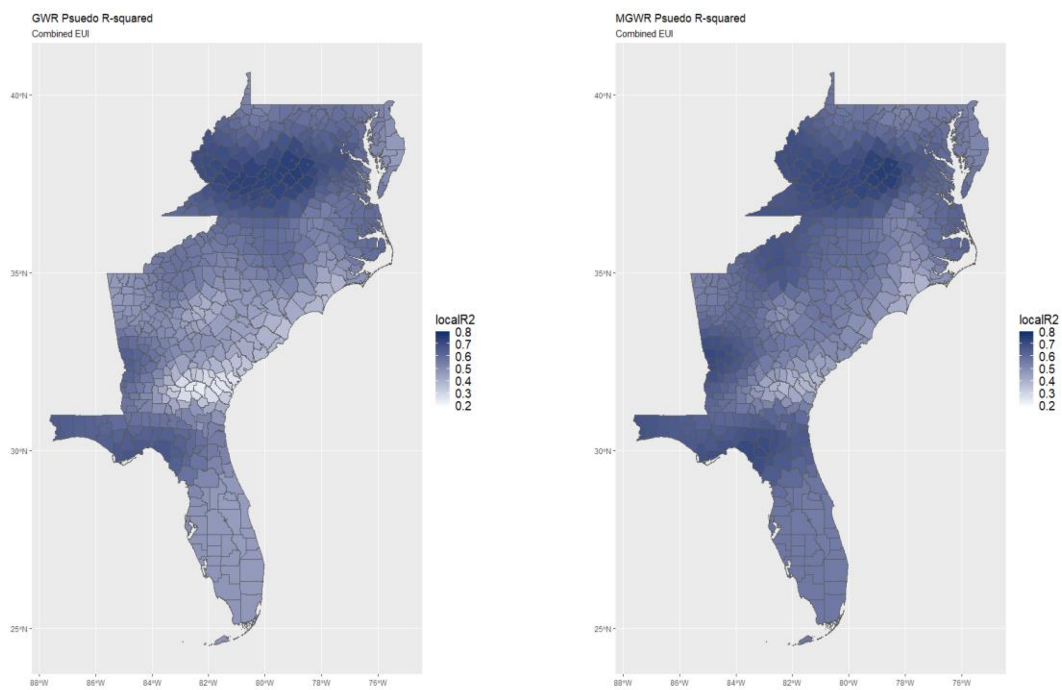
Table 4.4

Comparison of the Geographically Weighted Regression (GWR) and a Multiscale Geographically Weighted Regression (MGWR) variable statistics and bandwidths. A GWR fits the same bandwidth for all variables. An MGWR fits a separate bandwidth for all variables

	GWR						MGWR					
Variable	Mean	STD	Min	Median	Max	Bandwith	Mean	STD	Min	Median	Max	Bandwith
Intercept	0.07	0.86	-1.45	0.09	1.74	108	0.09	0.92	-1.79	0.21	1.73	43
% Age 25 + below HS education	-0.30	0.23	-1.16	-0.24	0.17	--	-0.27	0.03	-0.31	-0.28	-0.23	506
% Age 65+	0.16	0.28	-0.42	0.10	0.95	--	0.19	0.14	-0.02	0.14	0.49	148
% African American	0.27	0.26	-0.41	0.24	0.84	--	0.26	0.00	0.26	0.26	0.26	587
% Hispanic	0.09	0.16	-0.28	0.08	0.52	--	0.15	0.18	-0.40	0.11	0.73	43
% Poverty status last 12 months	0.13	0.18	-0.56	0.10	0.69	--	0.19	0.10	0.01	0.17	0.35	207
% with disability	-0.03	0.14	-0.32	-0.03	0.35	--	-0.04	0.07	-0.16	-0.05	0.17	163
median income	-0.08	0.28	-0.92	-0.03	0.60	--	-0.01	0.01	-0.02	-0.01	0.00	587
% below age 18	0.01	0.16	-0.45	0.03	0.40	--	0.04	0.07	-0.11	0.04	0.20	124
% renter occupied	0.13	0.21	-0.38	0.08	0.64	--	0.13	0.17	-0.10	0.08	0.50	141

Figure 4.3

Local R-squared values for GWR (left) and MGWRG (right) socioeconomic models. Value indicates the strength of the model at the given observation location.



A pseudo-R^2 term indicating model fit for every observation is reported for GWR and MGWR and can be mapped to designate the strength of both the GWR and MGWR model over the study area, showin in Figure 4.3. The pseudo-R^2 ranges from approximately .3 to .9 within the study area for the GWR and MGWR.

Coefficients of the GWR and MGWR model can be mapped to each county, along with significance, to identify areas where specific variables are influential to the local model. For each of the 9 variables, coefficient maps can be compared between the same variables for both. The mapped results show where the variable is important in explaining variation in the data and also compare how a change in bandwidth, and thus assumed scaled influence, changes the outcomes of the model, shown in Figure 4.4. Blue indicates a positive correlation between model terms and the normalized EUI, while red indicates a negative correlation. Non-significant coefficients are in white.

Coefficient Map Results

Percent African American

The GWR results for this variable showed relatively regional patterns, with multiple distinct groups across the study area. This includes a negatively associated relationship group near the Charlotte, NC area, the capital of North Carolina, located in the southeast portion of the state. The MGWR showed complete coverage of the variable across the study area, with relatively little difference in coefficient value indicating a global, homogenous relationship spatially.

Percent poverty status in last 12 months

The GWR results showed small significant areas in the northern part of the study area, including one small negative relationship in central North Carolina. The MGWR results showed a much broader, single positive significant area that stretched from Delaware to the panhandle of Florida.

Percent without a high school education

The GWR results showed three regional negatively associated groupings across the study area. Similar to Percent African American, the MGWR showed a much broader significant relationship across the entire study area indicating a homogenous, global spatial relationship.

Median income

The GWR results for this variable showed small significant areas, that were both positively and negatively associated with EUI. The MGWR indicated no significant areas across the study area, indicating median income was not significant or was captured by other variables when a multiscale approach was used.

Percent population over 65

The GWR results showed a large positive significant area in West Virginia and western Virginia. It also included some other smaller areas and one larger negative area around Charlotte, NC. The MWGR showed a large significant area in the northern part of the study area and no negative areas across the study area.

Percent Hispanic population

The GWR results showed a larger significant area in the northern part of the study area. Two smaller significant areas also indicated locally significant patterns. The MGWR results did not alter the patterns much but did more significant areas including south Florida.

Percent with disability

Percent with disability showed similar patterns in both the GWR and MGWR, including significant areas with negative and positive relationships. An area in the Florida panhandle that was significant was not in the MGWR.

Percent population under 18

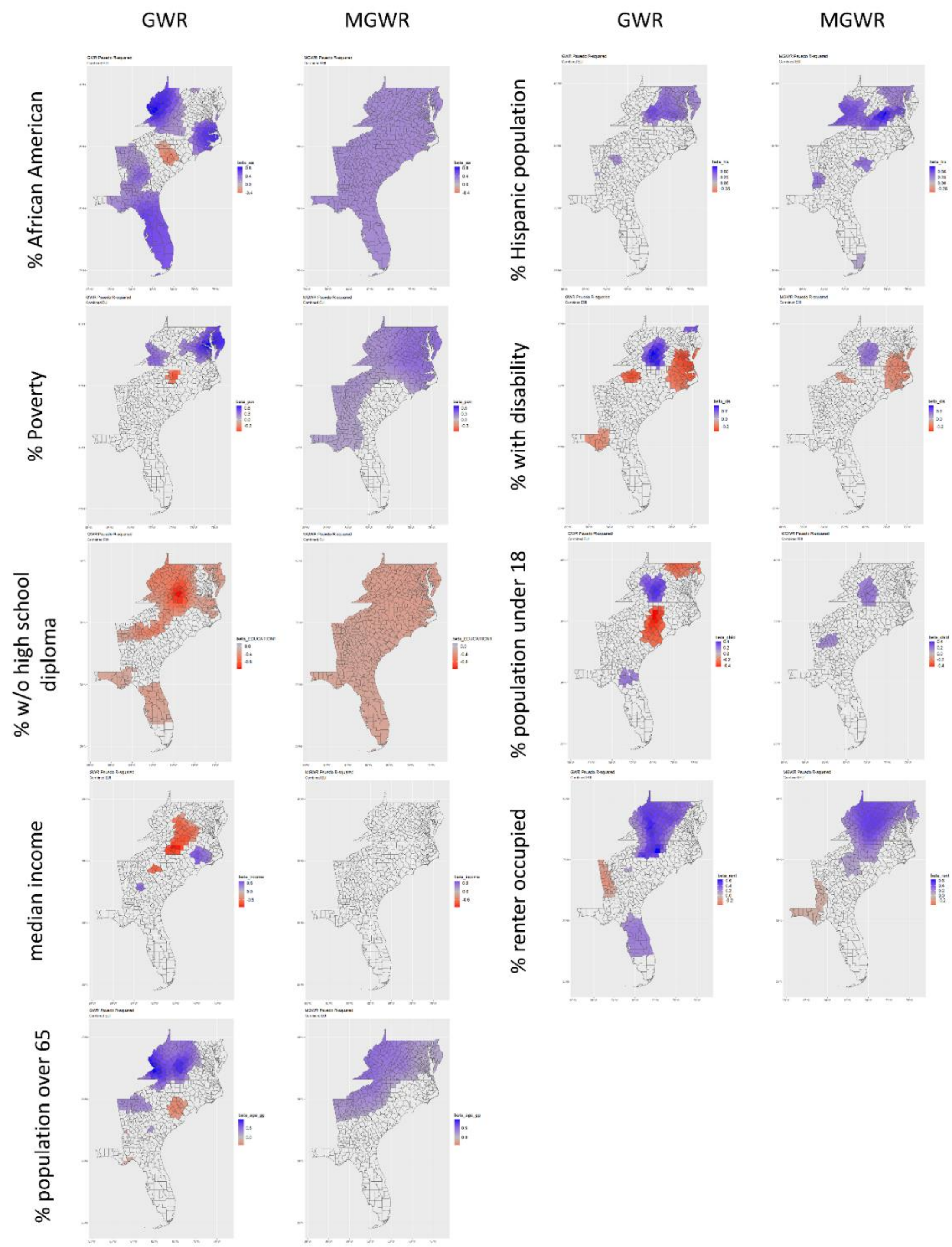
The GWR showed four major regional significant areas, both positive and negative. The MGWR results removed the negative results and one positive area was retained. Another positive area was significant near the Atlanta, GA area.

Percent households renter occupied

Percent renter-occupied showed similar patterns in both the GWR and MGWR, including significant areas with negative relationships in the southwestern portion of the study area and positive relationships in the northern part of the study area. A significant area in Central Florida in the GWR was not present in the MGWR.

Figure 4.4

Coefficient values for indicated variables for GWR (left) and MGWRG (right) socioeconomic models. Value indicates the strength of the variable at the given observation location. Red indicates a positive relationship between the variable and EUI, while blue indicates a negative relationship. White indicates a non-significant relationship.



Discussion

The purpose of this research is to explore the spatial justice implications of the spatial relationship between socioeconomic characteristics of energy poverty vulnerability. A modeled county-level estimation of EUI was used to approximate the energy burden for the study area. The use of the scaled energy burden estimation allowed spatial models to address scale as a component of energy poverty and the spatial justice outcomes that might occur. The observed relationship between selected socio-economic characteristics and EUI revealed an explicitly spatial, multi-scalar relationship. Little previous work has performed explicit spatial analysis on a EUI estimation, including both GWR and MGWR (Moore & Webb, 2022). Further, no work focuses on a multi-state region. Reames (2016), Bednar and Reames (2017), and Buyolva (2020) performed the analysis within an urban area, while Min et al. (2010) performed the analysis for the entire US, it was not associated with socioeconomic characteristics.

The results of the exploratory analysis point to some common refrains in energy poverty. First, energy poverty is both a local and regional issue that is compounded by many different attributes and structural patterns related to energy production and consumption (Bouzarovski & Simcock, 2017; Hernández, 2015). Second, scale plays a role in energy poverty in multiple ways (Bouzarovski & Simcock, 2017; Mashhoodi et al., 2019). Understanding what a vulnerability to energy poverty is in a household means understanding the context of interconnected social and physical processes occurring on multiple scales. Further, it means that policy addressing each of these processes is relevant, and connected, yet may not be recognized. Recognition through a policy of energy poverty is essential to the equity of energy policy (Gillard et al., 2017; Hernández, 2015), and we argue as part of that recognition, an effective policy at appropriate scales addresses the inequity in part.

Both the heating and cooling estimation models were strong overall fits, indicating the data selected as part of the EUI estimation models were sufficient. All HDD categories were the most important variables in estimating heating EUI in the given data, followed by wood and electricity heating. Mobile homes were also important in estimating EUI, showing a positive relationship with EUI in comparison to multi-family homes. The direction of the relationships for the structural variables selected is in line with previous studies on heating EUI (Bednar et al., 2017; Reames, 2016).CDD categories were also the most important in the cooling EUI model, along with housing type. Interestingly, income was also significant in the cooling model indicating that their cooling use might be more dependent on disposable income than heating.

Mapped EUI estimations show a strong north-to-south pattern, where EUI is higher in colder climates. *Weather* normalization maps shown in Figure 4.2 indicate that while colder areas are less efficient, they are not as extreme as a non-normalized EUI would suggest. It should be noted that these calculations are estimations of heating and cooling EUI, not total energy use in the household. While weather normalization is appropriate as heating and cooling are most dependent on climate effects, there are still non-climate energy uses, such as lighting, utilities, and water heating in a household that can affect the overall EUI of a house.

The multivariate relationship of socioeconomic characteristics had a low explanatory power of only 0.18 R2. This suggests the socio-economic variables selected together do not explain EUI fully. However, the variables selected are common indicators of energy poverty and were selected to explore the relationships, not to completely predict EUI. Further, using a global estimation, especially across multiple climates with EUI, makes it difficult to discern useful patterns.

There was a large increase in explanatory power between the OLS model and both spatial models (GWR, MGWR). The increased explanatory power coupled with the Moran's I indicates that across the study area the relationship is explicitly spatial. The model fit improvement of MGWR over GWR specifies the relationship is also scalar. In the context of an MGWR, a scalar relationship means the independent variables included in the model vary in the geographic scale of their relationship with EUI (Oshan et al., 2020). This also provides a foundation for framing the justice implication of the energy burden – socioeconomic relationship. The relationship between energy burden and socioeconomics shifts based on location, indicating that injustices may also derive from location and scale in some capacity.

All variables except percent poverty and percent renter-occupied were significant at a 0.1 level in the socioeconomic OLS regression, which does not take location into account. While the explanatory power of the model was relatively low the selected variables are important to explaining EUI in the region. However, some explanatory variables were possibly omitted from the study areas. Percent Hispanic was the variable of most importance in the model.

Estimation of socioeconomic characteristics of EUI across a broad geographical range can be difficult with a non-spatial model such as an OLS. The direction of the relationships for many of the variables was not expected as would be in much of the literature (Bednar et al., 2017; Moore & Webb, 2022; Reames, 2016). All variables included were expected to increase EUI except median income, which may also change based on location or area. The sign inconsistency could be for two reasons. First, not every aspect of energy use intensity is included in the model. The purpose of the regression was to formulate a multivariate understanding of the socioeconomic context of EUI across the region. A variable omission may explain in some parts the sign change. Second is the assumption of independence of the observations. A Moran's I test indicated there was spatial autocorrelation, which drives observations near each other to be more similar regardless of independent variable measurements. These both can affect the direction of the relationships. The spatial models corrected the direction of the relationships to the expected values. However, one variable percent of those aged 25+ without a high school degree retained a negative relationship with EUI. This relationship may also be due to variable omission over the study area.

The GWR model is optimized at the lowest AICc with a bandwidth of 108 counties. With a total of 588 counties in the study area, 108 is a relatively small bandwidth. For reference, North Carolina contains 100 counties. A smaller GWR bandwidth indicates that taken together, the socioeconomic characteristics interact at a relatively local scale in comparison to the study area, where only the nearest 108 counties are influencing the calculation of any given county. An MGWR relaxes the assumption all socioeconomic processes are occurring at the same geographic scale, and therefore will vary. The bandwidth is an important spatial justice concept as part of the model. The optimum bandwidths for the MGWR socioeconomic characteristics varied from 43 counties to 587 counties or the entire study area. This can be interpreted as a small bandwidth indicating the relationship varies locally, while a large bandwidth indicates that regardless of the location the characteristic is an indicator of EUI. Percent Hispanic was the only independent variable to have a bandwidth below 100 counties, showing that the relationship of the percent Hispanic population with EUI by location varies greatly within the study area. In contrast, both percent African American and median income had bandwidths of 587, indicating a homogenous interaction across the study area with the two variables and EUI. Differentiation between scaled relationships indicates that the original GWR bandwidth may not appropriately allow the variables to interact at the appropriate scale at which they occur. Five of the variables included in the spatial socioeconomic models did not change bandwidth significantly from the GWR: percent Age 65+, percent poverty status last 12 months, percent with a disability, percent below age 18, and percent renter-occupied, indicating a regional relationship. All five regional variables were within a bandwidth change of 100 counties, and notably all increased bandwidth. This is most likely due to the strong influence of the percentage Hispanic population reducing the bandwidth, with the moderate size of the remaining variables balancing the size of the bandwidths.

Bandwidth selection for both the GWR and MGWR are spatial in that they provide an estimation of how local or global the influence of a variable is across the study area. However, bandwidths do not alone provide locations of the influence. Comparison of local coefficient maps and significance for each of the variables included in the GWR and MGWR can provide visual insight into the spatial relationship between socioeconomic characteristics and EUI. As a spatial justice component, this allows understanding both the distributive justice effects of energy burdens and the possible energy outcomes based on these relationships. Many of the spatial patterns for significant coefficients did not change for variables that also did not change bandwidths (percent Age 65+, percent poverty status last 12 months, percent with a disability, percent below age 18, and percent renter-occupied).

Coefficient maps for percent renter-occupied, percent over 65, and percent in poverty showed multi-state regional spatial patterns for both GWR and MGWR models and often in the northern part of the study area, indicated in Figure 4.4. This may be in part due to the influence of colder climates on EUI in the northern states. This supports relatively moderate bandwidth selection, indicating a regional influence of the variables. Percent poverty was the largest bandwidth change between the GWR and MGWR of the five moderately increasing variables. It was not significant in the OLS model but was influential across the study area in the spatial models. This indicates that poverty was highly localized and a global OLS model would not sufficiently capture the spatial variable across the study area.

Percent Hispanic population was the only variable to decrease bandwidth between the GWR and MGWR. The decrease indicates that the relationship between the Hispanic population and EUI is local This pattern is reflected in the coefficient maps, where local areas of significance are more apparent, especially in the Northern states and some smaller southern areas, such as Columbus, Georgia; Charleston, South Carolina, and Southern Florida which have a higher percentage of Hispanic populations.

Three variables, percent African American, percent Age 25 + below HS education, and median income, increased bandwidth to above 500 from the GWR to the MGWR. The increase in bandwidth indicates that these variables have a much more homogeneous relationship with EUI across the study area. The coefficient maps of the area have a similar result. African American population showed a small but significant coefficient for the entire study area, in contrast to the more varied coefficient values in the GWR, this indicates regardless of area, an increase in African American population was related to an increase in EUI. Percent without a high school diploma showed a similar result, however, the negative relationship across the area indicates it may be explaining population variation that other variables are not picking up. While income did increase in bandwidth, it became non-significant in the study, indicating that other variables capture the variance of income.

The outcomes of this work indicate many possible spatial justice concerns with implications for energy poverty policy. First, the geographic extent of the process, or variables, play an important role in both highlighting where injustices are occurring and appropriate policy interventions. Bandwidths are used as a proxy for the geographic scales of processes in both models, and identifying them through the MGWR and GWR provides a basis for comparison. The first spatial justice concern is the differences in scale of the variables. The GWR bandwidth is about 1/6 of the total area. This indicates that taken together, the socioeconomic variables are effective at explaining the relationship at a bandwidth of around 100 counties. This means that the modeled relationship in Southern Florida for example is not influenced by the relationship in Delaware. This intuitively makes sense as the geographic distance means that climate, housing, and population characteristics will be different. Compared to a global model, which assumes all variables are important everywhere, the GWR allows for spatial nuance in addressing the relationships

The varying bandwidths of the MGWR indicate a further spatial justice concern. Results of the MGWR show the scale of the relationship between socio-economic characteristics and EUI varies. This confirms that assuming the scale is the same for every variable ignores the possible influence the variable has. The scale variation reshapes the link between energy poverty conceptualization of distributive justice. The MGWR process defines an individual bandwidth for each variable and where that variable is significant. Therefore bandwidth optimization, or the determination of the geographic extent of the spatial process, plays an important role in determining where injustices are occurring. Just policy addressing the distribution of energy burdens must attend to processes as spatially varying and occurring at different scales. Distributive justice for energy poverty is both scales of process and location.

Further, just procedural solutions address both scale and location as aspects of distributive injustice. Patterns emerging at a small geographic scale are more likely to have relative changes that are more substantial moving from location to location, indicating localized solutions may take priority. In contrast, a large-scale pattern indicates a much larger area of influence. Policy addressing patterns at a large scale may be more appropriate.

Large-scale, multi-state patterns suggest collaboration between entities such as utilities, community agencies, and state governments. It also means that federal action may be more appropriate. The Hispanic population patterns show a small bandwidth coupled with multiple areas of significance, meaning many small but important areas should be addressed between energy burden and Hispanic residents. The African American population showed a global pattern, where the bandwidth was the entire study area and was significant in all locations. Lastly, these results suggest recognition of the scale of variables in analyses is an important aspect of spatial energy justice work. Recognition of local and global processes means differentiating how to interpret distributive outcomes and policy attempts. Thus the three tenets of energy justice do not occur absent from one another.

For variables that were homogeneous across the study area, addressing them on a local level is important, but might not structurally solve the core issues. For example, the relationship of the African American population to EUI across the study area is nearly the same everywhere. This pattern might indicate a prevalence of structural racism in the US as a cause, but also indicates that the relationship should be given weight in all geographic areas. This becomes a policy dilemma of scale, where local interventions like zoning, local funding for house retrofits, etc. can be specific and efficient but are not comprehensive across a broader geographic area. However, the federal recognition of energy poverty in the US is poor and guidelines to recognize the many forms of energy poverty are nearly non-existent (Bednar & Reames, 2020). As a first step to addressing recognition as a spatial energy justice issue, flexibility in energy poverty legislation is paramount. Identifying the specific location and scale of multiple issues and allocation funding based on these outcomes can allow local and federal government legislation to effectively scale interventions as needed. The results of this work show that the many components of energy poverty are multi-scalar and addressing them as such is required for just policy.

It should be mentioned that this study does not preclude awareness of patterns occurring in areas that are not highlighted. This work seeks to understand how geography influences both what patterns might be most important, and how addressing energy poverty in specific areas may misrepresent other vulnerabilities that are occurring.

Conclusion

Through the development of a EUI estimation from publicly available microdata, we identified the relationship of socioeconomic characteristics to EUI across the Eastern US. Through a geospatial analysis, these relationships overall showed a positive relationship in many areas of the study area, confirming previous studies of an increase in EUI associated with the characteristics. The geospatial analyses provided some insight into the spatial patterns of socioeconomic characteristics and relationship EUI in the Eastern US, in particular the scale of the relationship. An MGWR analysis signified that the socioeconomic processes occurring across the area may be occurring at different scales simultaneously (Oshan et al., 2019, 2020). Focusing on the scale of influence for each indicator allows for the differentiation of local or regional patterns. These results drive the discussion of the intent of energy poverty policy to overcome the limitations that either a global or local policy has to address energy poverty. If the intent is to address energy poverty at a multi-state or federal scale, addressing EUI relative to the increase in the African American population is most appropriate for a broad impact. If the intent is to address energy poverty at a state level, regional patterns such as renters might be a more appropriate avenue as the effect would be appropriate for the area. The same for local policy impacts and the Hispanic population. Tailoring interventions to appropriate scales will increase the ability to provide just policy. Further, these techniques can be used to validate the equity in existing interventions, comparing how state and local policies are targeting areas of need. Federal funds for energy poverty assistance are often funneled through entities acting at specific geographies (a county for example). Addressing where these funds would be best served, and at which scale would allow for addressing energy poverty from multiple scales at once. This work highlights scalar differences to provide spatial energy justice contexts to the importance of locally specific and regionally specific policy. Equity results from recognizing patterns that might not otherwise be apparent. Further, it highlights the need for an increased but flexible approach to energy poverty in the US, where there is a lack of recognition of energy poverty overall, and where singular policies at one scale will not address energy poverty efficiently.

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CHAPTER 5: CONCLUSION

This dissertation and the three chapters within provide a unique exploration into the use of spatial analysis to identify areas to improve just energy poverty policy. Specifically, they offer contributions to the field of energy poverty by incorporating a justice framework into the spatial analysis of energy poverty. Chapter 2 incorporates a first attempt in the field at defining spatial analysis of energy poverty as a subset of the field and provides the groundwork for new directions. Chapter 3 is one of the first spatial energy poverty papers to use a set of multi-scale analyses of energy poverty, taking inspiration from Robinson et al. (2019) and Fahmy et al. (2011). This is also the first paper to perform a Geographically Weighted Principal Components Analysis (GWPCA) at multiple scales providing a template for rethinking energy poverty policy. Chapter Four is one of the first to downscale 2015 Residential Energy Consumption Survey data (EIA, 2015) to the county level. This was used in a relatively new spatial analysis technique, a Multiscale Geographically Weighted Regressions (MGWR), that has been performed only a handful of times and not to a spatial extent as large as the east coast of the US. The combination of these techniques combined with the understating that energy poverty is a spatial phenomenon that changes as spatial context changes, means that we can begin to recommend policy attentive to these contexts.

Chapter 2 introduced a semi-systematic literature review, filling a gap in the spatial energy poverty field. The review provides an overview of seven key variables describing data selection, methodology, and location of research in the field. It highlights areas of potential bias, such as a significant number of papers focusing on European research locations and an overreliance on government data in spatial analysis. It also revealed that census-tract level work was a common scale of analysis. This indicates overreliance on single-location, single-source data. The recommendations provide ways to combat these biases and provide a more just policy and research.

Chapter 3 introduces a set of methods to understand how geographic scale changes energy poverty identification. An unintended consequence of misuse of scale is misidentifying or excluding households with unique energy poverty patterns. Using a PCA and a GWPCA at multiple scales, multiple energy poverty signatures were revealed at each scale. Some were *scale-dependent*, indicating they only are revealed when analyzed at a specific scale. Others were *scale-agnostic*, indicating they transcend scale and are important in multiple areas. Using the Weatherization Assistance Program (WAP) and the US infrastructure bill as a frame, I suggest reframing the allocation and funding of current policy should be reframed to allow for more spatial specific contexts to attend to underrepresented or missed energy poverty signatures.

Chapter 4 uses two models to both downscale energy use data to a county level and identify the scale of socio-economic characteristics interacting with energy use. The results showed that some characteristics showed both small and large-scale interactions simultaneously. This indicates that to address energy poverty, a policy must be flexible to multiple scales. This means both community and federal policy must work simultaneously to address energy poverty as they pertain to the spatiality of the social processes occurring.

Scale and location are vital components of any research. When addressing injustice in resource management, the lack of attentiveness to these spatial aspects can lead to the misidentification of those in need. This work provides an invaluable resource to address spatial energy justice in applied spatial analysis to rethink approaches to energy poverty eradication.

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