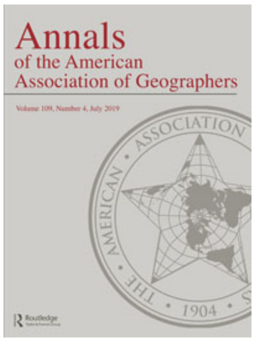

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The Spatially Varying Components of Vulnerability to Energy Poverty

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A household's vulnerability to energy poverty is socially and spatially variable. Efforts to measure energy poverty, however, have focused on narrow, expenditure-based metrics or area-based targeting. These metrics are not spatial per se, because the relative importance of drivers does not vary between neighborhoods to reflect localized challenges. Despite recent advancements in geographically weighted methodologies that have the potential to yield important information about the sociospatial distribution of vulnerability to energy poverty, the phenomenon has not been approached from this perspective. For a case study of England, global principal component analysis (PCA) and local geographically weighted PCA (GWPCA) are applied to a suite of neighborhood-scale vulnerability indicators. The explicit spatiality of this methodological approach addresses a common criticism of vulnerability assessments. The global PCA reaffirms the importance of well-established vulnerabilities, including older age, disability, and energy efficiency. It also demonstrates striking new evidence of vulnerabilities among precarious and transient households that are less well understood and have become starker during austerity. In contrast, rather than providing a single estimate of propensity to energy poverty for neighborhoods based on a national understanding of what drives the condition, the GWPCA identifies a diverse array of vulnerability factors of greatest importance in different locales. These local results destabilize the geographical configurations of an urban–rural and north–south divide that typify understandings of deprivation in this context. The geographically weighted approach therefore draws attention to vulnerabilities often hidden in policymaking, allowing for reflection on the applicability of spatially constituted methodologies to wider social vulnerability assessments. *Key Words: energy poverty, geographically weighted PCA, GIS, spatial analysis, vulnerability.*

家户对能源匮乏的脆弱性，在社会与空间上具有变异。测量能源匮乏的努力，却仅聚焦狭义且以花费为基础的度量、抑或根据地区的目标。这些度量本身并不具空间性，因其驱力的相对重要性，在邻里之间并不存在差异，以反映在地化的挑战。尽管晚近地理加权方法的进展，具有生产有关能源匮乏脆弱性的社会空间分佈之重要信息的潜能，但该现象却尚未从此一视角进行分析。英格兰的案例研究中，全球主成分分析（PCA）和地方地理加权PCA（GWPCA）应用于一套邻里尺度的脆弱性指标。此一方法的显着空间性，应对脆弱性评估的一个普遍批评。全球PCA再次确认了根深蒂固的脆弱性之重要性，包括较为年长、残疾、以及能源效率。该方法同时证明不稳定和暂时性家户的脆弱性之崭新惊人证据，该现象较不为人所知，且在撙节时期变得更为显着。与根据驱动能源匮乏的全国性理解来提供邻里的能源匮乏倾向之单一评估相反的是，GWPCA指认不同地方中最为重要的多样脆弱性因素。这些在地结果，颠覆了城乡与南北区隔的地理组成，该组成是在此脉络中对于匮乏的典型理解。地理加权方法因此引起对于经常隐藏于政策制定中的脆弱性之关注，并促成对于将空间上构成的方法应用于更广泛的社会脆弱性评估的反思。*关键词: 能源匮乏，地理加权 PCA，地理信息系统，空间分析，脆弱性。*

Una vulnerabilidad del hogar a la pobreza energética es variable social y espacialmente. Los esfuerzos para medir la pobreza energética, sin embargo, se han enfocado sobre estrechas métricas basadas en gasto, o en orientación basada en área. En sí mismas estas métricas no son espaciales, en cuanto la importancia relativa de los controladores no varía entre los vecindarios para reflejar los retos localizados. A pesar de los avances recientes en metodologías geográficamente ponderadas, que tienen el potencial de generar información importante acerca de la distribución socioespacial de la vulnerabilidad a la pobreza energética, el fenómeno no ha sido abordado desde esta perspectiva. Para un estudio de caso de Inglaterra, el análisis de componentes principales global (PCA) y el PCA local geográficamente ponderado (GWPCA) fueron aplicados a un

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paquete de indicadores de vulnerabilidad a escala de vecindario. La espacialidad explícita de este enfoque metodológico aboca una crítica común de las evaluaciones de vulnerabilidad. El PCA global reafirma la importancia de vulnerabilidades bien establecidas, incluyendo edad avanzada, discapacidad y eficiencia energética. Demuestra también una sorprendente evidencia nueva de vulnerabilidades entre hogares precarios y temporales que son menos entendidos y que se han endurecido aún más en la austeridad. Por contraste, en vez de proveer un cálculo sencillo de propensidad a la pobreza energética en vecindarios basados en un entendimiento nacional sobre lo que maneja la condición, el GWPCA identifica un surtido de factores de vulnerabilidad de la mayor importancia en diferentes localidades. Estos resultados locales desestabilizan las configuraciones geográficas de una divisoria urbana–rural y norte–sur, que tipifica los entendimientos de privación en este contexto. En consecuencia., el enfoque geográficamente ponderado atrae atención hacia vulnerabilidades a menudo escondidas en el diseño de políticas, permitiendo la reflexión sobre la aplicabilidad de metodologías constituidas espacialmente para evaluaciones más amplias de vulnerabilidad social. *Palabras clave: análisis espacial, PCA geográficamente ponderado, pobreza energética, SIG, vulnerabilidad.*

Energy poverty in the home has attracted considerable attention in research, policymaking, and practice during recent years (Liddell et al. 2012; Boardman 2013), and this interest is becoming increasingly global (Harrison and Popke 2011; Thomson and Snell 2013; Okushima 2017; Sadath and Acharya 2017). Subsequently some of the stark, relative inequalities in access to domestic energy services that exist between and within different national contexts (J. Healy 2003; Thomson and Snell 2013) and among varied household types have been highlighted (e.g., Ambrose 2015; Gillard, Snell, and Bevan 2017; Petrova 2017). Such attention is important given the negative impacts of energy poverty on health and well-being (Liddell and Morris 2010) and the interrelations between tackling energy poverty and reducing carbon emissions (Urge-Vorsatz and Tirado Herrero 2012).

Recently, the sociospatial vulnerability that gives rise to energy poverty has become a research focus (Hall, Hards, and Bulkeley 2013; Bouzarovski et al. 2017; Bouzarovski and Thomson 2018), drawing attention to the multifaceted nature of this type of vulnerability and how it is "highly geographically variable and locally contingent" (Bouzarovski 2014, 282). In combination with concepts of justice (G. Walker and Day 2012), capabilities (Day, Walker, and Simcock 2016), and precarity (Petrova 2017), vulnerability framings have opened up relatively narrow debates ongoing in policymaking to reveal different household types and geographies within which energy poverty is likely to manifest (Bouzarovski and Petrova 2015; Middlemiss and Gillard 2015). Acknowledgment of the importance of place is also apparent in research concerned with the distribution of vulnerability to other types of global environment change (Cutter, Boruff, and Shirley 2003; Cutter and Finch 2008). Here, a vulnerability index has frequently been derived to understand the sociospatial distribution of vulnerability at a regional or neighborhood scale. Methodologically, vulnerability indexes have often used principal component analysis (PCA), a statistical analysis that reduces a large, multivariate set of vulnerability indicators into principal components, allowing for the assessment of relative vulnerability between small areas (Jolliffe 1986). However, recent advancements in spatially constituted methodologies such as geographically weighted PCA (GWPCA) (Harris et al. 2011; Demšar et al. 2013; Gollini et al. 2014; Lu et al. 2014) provide an opportunity for PCA-based vulnerability assessments to be explicitly spatial, accounting for the effect of surrounding locales on vulnerability in an area. This addresses a common critique of existing vulnerability indexes (Frazier, Thompson, and Dezzani 2014; Chang and Chen 2016).

With these debates in mind, our aims are twofold: (1) to understand the sociospatial distribution of vulnerabilities that enhance energy poverty and (2) to investigate the applicability of spatially constituted methodologies to understanding vulnerability to energy poverty and subsequently other types of social vulnerability. To achieve these aims, a vulnerability index that incorporates both traditional and geographically weighted PCA is developed for a case study of England, a devolved administration in the United Kingdom. Rather than providing a single estimate of propensity to energy poverty for neighborhoods based on a national understanding of what drives the condition, like many existing area-based estimates, the approach highlights the vulnerability factors likely to be of greatest importance in enhancing energy poverty in different locales. It allows for recognition of how the relative importance of vulnerability factors varies geographically, for example, between urban and rural regions (Roberts, Vera-Toscano, and Phimister 2015), more or less affluent areas, or neighborhoods characterized by housing of varying efficiency (Dowson et al. 2012). Thus, the analysis makes visible a diverse array of geographies associated with vulnerability to energy poverty, including those that tend to be hidden when policymakers and practitioners tackle this form of deprivation (Buzar 2007).

Sociospatial Vulnerability to Energy Poverty

Energy poverty is the condition in which a household is unable to access the domestic energy services (e.g., heating, lighting, cooling) sufficient to ensure their well-being and allow them to participate meaningfully in the society in which they live (Buzar 2007). Energy poverty is distinct from wider forms of poverty due to the role of domestic and networked energy infrastructures in its manifestation (Boardman 1991). Boardman (2012), whose work first inspired interest in energy poverty in the British context, emphasized the difference between its symptoms and the causes. As noted, being without socially necessitated energy services has negative impacts on physical and mental health, educational opportunities, and social relations (Liddell and Morris 2010), outcomes that can be termed the *symptoms* of energy poverty. Many of these symptoms are common among energy-poor households and have been extensively researched, including the physiological impacts of cold homes on health leading to excess winter deaths (Clinch and Healy 2000). Identifying the *causes* of energy poverty is more complex due to recognition of the multidimensional drivers that can enhance the condition (Dubois 2012).

Vulnerability is an established concept when seeking to understand the likelihood of negative consequences arising from global environmental change (Cutter 2003; Adger 2006). We draw on the definition of *vulnerability* as the "degree of susceptibility to … stresses, which is not sufficiently counterbalanced by capacities to resist negative impacts in the medium to long term, and to maintain levels of overall wellbeing" (Allen 2003, 170). The degree of susceptibility to a stress, in this case a lack of socially necessitated energy services, varies socially and spatially (Cutter, Boruff, and Shirley 2003; Cutter and Finch 2008; Lindley et al. 2011).

In theorizing vulnerability to energy poverty, Bouzarovski and Petrova (2015) identified various vulnerability pathways via which a household becomes energy poor, and Middlemiss and Gillard (2015) assessed household vulnerability from the bottom up. These assessments have helped to articulate the importance of place, pinpointing how the relative contribution of a diverse range of vulnerability factors varies between locales. Understanding of the spatialities of energy vulnerability was furthered by Bouzarovski and Thomson (2018), who derived a neighborhood-scale typology of energy vulnerability using household-scale survey data. Vulnerability to energy poverty is subsequently recognized as a highly sociospatial phenomenon (Bouzarovski et al. 2017).

Building on vulnerability debates, the concept of precarity explores the structural causes of energy poverty, drawing attention to the wider political, socioeconomic, institutional, and cultural processes that shape those factors that render people vulnerable and impoverished (Petrova 2017). Examples of structural drivers include insecurities in labor and housing markets in addition to the cultural and institutional making of new energy needs. Structural precarities are also highly locally specific, manifesting to differing extents in areas with varied sociospatial characteristics.

In differentiating between the relative vulnerability of households and places to energy poverty, a variety of personal, socio-economic, sociotechnical, and institutional factors are documented, including low incomes, high energy prices, energy inefficiency within the built environment, above-average energy needs, inflexibility and precarity concerning living arrangements, a lack of social networks, and unhealthy energy-related practices in the home that affect how efficiently energy is consumed (Bouzarovski and Petrova 2015; Middlemiss and Gillard 2015). In England (and increasingly across Europe, New Zealand, and the United States) several vulnerability factors are well understood. The physiological vulnerability related to sufficient warmth among the elderly, young children, and those with a disability or illness; the role of low incomes and high energy prices; and the legacy of inefficient housing stock are all recognized within a national strategy, "Cutting the Cost of Keeping

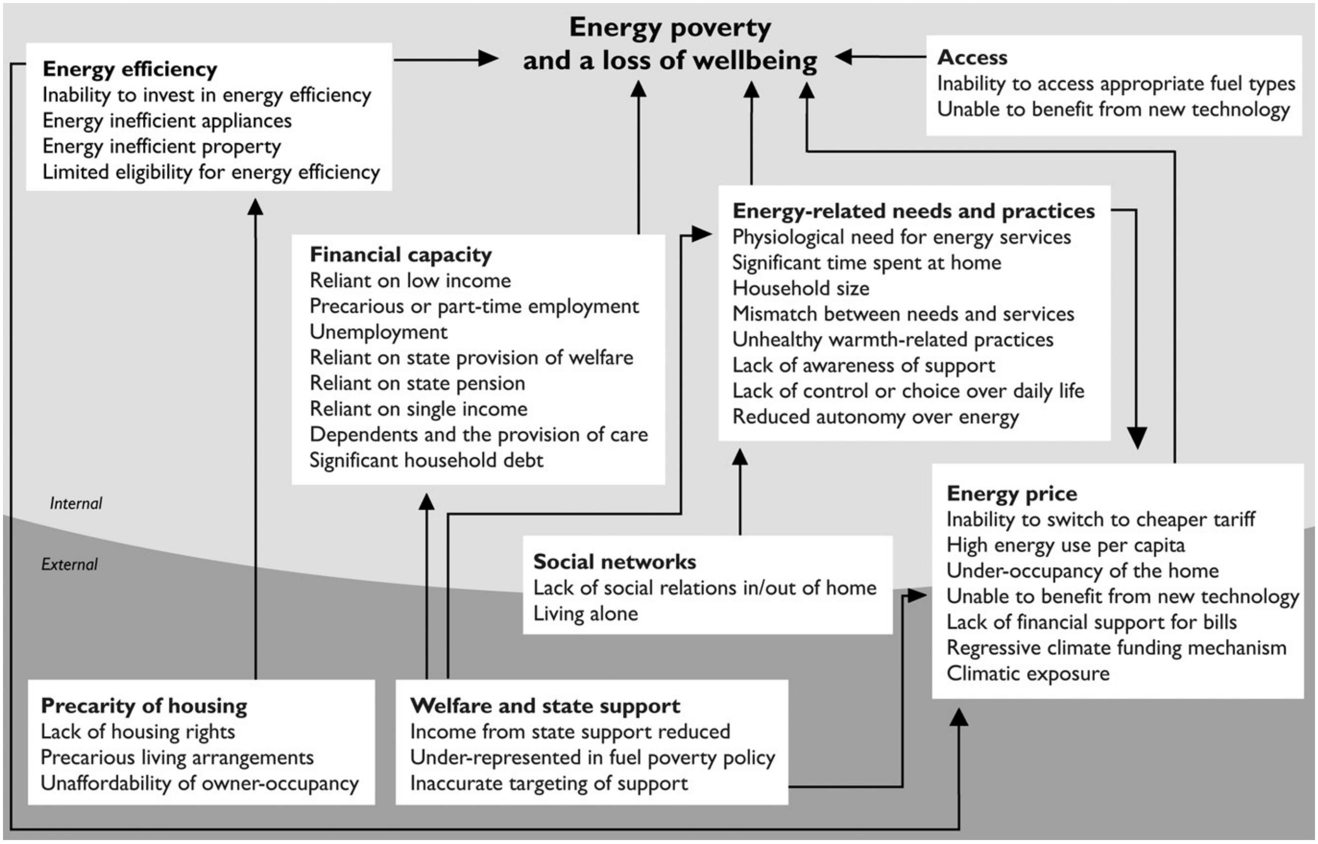


Figure 1. Vulnerability to energy poverty. The diagram maps out vulnerability factors that are both internal and external to the home that give rise to the condition of energy poverty and subsequent losses of well-being. Inspiration for the figure is drawn from conceptualizations of vulnerability to energy poverty offered by Bouzarovski and Petrova (2015) and Middlemiss and Gillard (2015) and the concept of precarity defined by Petrova (2017).

Warm" (Department for Energy and Climate Change [DECC] 2015). There are also less well-understood vulnerability factors that research has recently drawn attention to, including a more complex understanding of energy-related needs among people with a disability, those with poor physical and mental health, or providers of unpaid care (Snell, Bevan, and Thomson 2015). Changes within housing provision over the last three decades have led to the manifestation of vulnerability among people experiencing housing-related precarity, particularly those reliant on the private rental sector (Ambrose 2015). Additionally, the impact of austerity and public service cuts has increased low wages and unstable employment, including in-work poverty (Bennett 2014). These precarities have disproportionately affected certain households, including households with a member with a disability or illness, families with young children, and lone-parent families hit by rising living costs and benefit freezes (Millar and Ridge 2018). They are also more likely to affect young people (Butler and Sherriff 2017; Petrova 2017) and transient households including ethnic minorities (Bouzarovski 2014).

Figure 1 synthesizes these debates into a common framework outlining vulnerability factors derived from a review of existing qualitative research on vulnerability to energy poverty (Robinson, Bouzarovski, and Lindley 2018). The framework recognizes factors that give rise to the condition of energy poverty and subsequent losses of well-being that are both internal and external to the home.

Existing Analyses of the Spatial Distribution of Energy Poverty

Given this research agenda, Liddell et al. (2012) advocated for an increasingly multidimensional approach to measuring and mapping the distribution of energy poverty to reflect the local realities of the condition. Several examples of research exist that analyze the distribution of energy poverty in different geographical contexts. Among European Union (EU) member states, in the absence of standardized definitions, Thomson and Snell (2013) quantified the prevalence of energy poverty using consensual indicators. At a subregional scale, policymakers tend to use expenditure-based indicators to estimate the number of energy-poor households, most commonly the 10 percent and low income high costs indicators (Boardman 1991; Hills 2012). In England, these indicators are intended to inform the allocation and evaluation of alleviation policies; however, analysis at a neighborhood scale has found that they prioritize specific geographies (Robinson, Bouzarovski, and Lindley 2017) and demographics (G. Walker and Day 2012).

Several studies have identified neighborhoods of greatest need to support area-based targeting of energy poverty resources, often in tandem with existing indicators in which they have been extremely valuable (Fahmy and Gordon 2007; Fahmy, Gordon, and Patsios 2011; R. Walker et al. 2012; Reames 2016). In addition to being restricted by the narrow framing of existing indicators, however, these approaches are not spatial per se, because the importance of the drivers that enhance energy poverty in each area is determined at a national level rather than varying to reflect localized challenges (Fahmy, Gordon, and Patsios 2011). Fahmy, Gordon, and Patsios (2011) recognized that "the social and spatial distribution of fuel poverty varies considerably depending upon the specific definition and measurement approach adopted, and these considerations also have significant implications for our understanding of the 'geography of fuel poverty'" (4374). Different measurement approaches can therefore obscure or reveal different geographies, losses of well-being, and injustices associated with energy poverty (Boardman 2012; Robinson, Bouzarovski, and Lindley 2017; Robinson 2018).

Subsequently, our analysis fulfills a different aim. Given the significant advancement in qualitative understandings of vulnerability to energy poverty and in spatially constituted methodologies that allow us to account for the effect of surrounding locales on these relationships (GWPCA), the aim of this article is to understand the sociospatial distribution of vulnerabilities that enhance energy poverty. Rather than providing a single estimate of propensity to energy poverty for neighborhoods based on a national understanding of what drives the condition, our analysis draws attention to the diverse vulnerability factors likely to be of greatest importance in enhancing energy poverty in different neighborhoods. With this in mind, we discuss our conceptual and methodological approach to mapping the sociospatial distribution of vulnerability to energy poverty.

An Index of Sociospatial Vulnerability to Energy Poverty

Evidence of the multiple vulnerability factors that make a household more likely to fall into energy poverty (Dubois 2012; Bouzarovski and Petrova 2015; Middlemiss and Gillard 2015) directs us toward the use of a multidimensional suite of indicators (Fahmy, Gordon, and Patsios 2011; Liddell et al. 2012; R. Walker et al. 2012). These indicators can be difficult to organize, analyze, and visualize. Within global environment change research, an index of social vulnerability is an established approach for dealing with this multidimensionality, aggregating indicators in a meaningful way to investigate the relative importance of indicators and the distribution of vulnerability (Cutter, Boruff, and Shirley 2003). To overcome the assumption that people are equally vulnerable, vulnerability is often conceptualized within these indexes as a combination of social inequalities and inequalities of place, thus helping to understand the sociospatial distribution of vulnerability. For Eakins and Luers (2006), this approach concerns the "mapping [of] the theoretical determinants of vulnerability in an effort to illustrate spatially the distribution of different capacities and sensitivities" (376). It allows for questions to be posed about geographic space, such as, "Where are vulnerable people located?" in addition to social space, such as "Who in these places is vulnerable?" (Cutter, Boruff, and Shirley 2003).

Drawing inspiration from these methodologies, an index of vulnerability to energy poverty is derived, focusing on a case study of England. A significant body of qualitative research exists concerning vulnerability to energy poverty in this context, enabling the development of a conceptually rich vulnerability index. Both our methodological approach and our findings can be meaningfully applied in other national contexts, however, because considerable synergies have been recognized in the drivers of energy poverty globally (Bouzarovski and Petrova

Table 1. Vulnerability factors and indicator data sets

Indicator	Associated vulnerability factors[a]	Reference	Indicator data set
Older old	Inability to access appropriate fuel types; less able to benefit from new technologies; dependents and provision of care; high energy use per capita; physiological need for energy services; spend large proportion of time at home; unhealthy warmth-related practices; lack of awareness of support; lack of control and choice over daily lives; reduced autonomy over energy services; lack of social relations in/outside home; living alone	Day and Hitchings (2011), J. D. Healy and Clinch (2004), Wright (2004), O'Neill, Jinks, and Squire (2006), Ormandy and Ezratty (2012), Chard and Walker (2016)	Households with at least one person over 75 years[b]
Young children	Dependents and provision of unpaid care; high energy use per capita; lack of financial support for energy bills; under- or misrepresented in policymaking; physiological need for energy services; spend large proportion of time at home; large household size; lack of control and choice over daily lives; lack of social relations in/outside home	Bhattacharya et al. (2003), Yohanis et al. (2008), G. Walker and Day (2012), O'Sullivan et al. (2016)	Households with young children 4 years or below[b]
Disability or limiting illness	Reliant on state provision of welfare; high energy use per capita; lack of financial support for energy bills; income from state support reduced; under- or misrepresented in policymaking; physiological need for energy services; spend large proportion of time at home; mismatch between needs and services; lack of control and choice over daily lives; lack of social relations in/outside home	G. Walker and Day (2012), George, Graham, and Lennard (2013), Snell, Bevan, and Thomson (2015), Gillard, Snell, and Bevan (2017)	Persons whose day-to-day activity is limited a lot[b]
Lone parent	Precarious or part-time employment; reliant on a low income; reliant on a single income; dependents and provision of unpaid care; under- or misrepresentation in policy; spend large proportion of time at home; lack of control and choice over daily lives	J. D. Healy and Clinch (2004), Gingerbread (2013)	Household with lone parent and dependent children[b]
Part-time employment	Precarious or part-time employment	Snell, Bevan, and Thomson (2015), Petrova (2017)	Persons 16–74 years old in part-time employment[b]
Retired		J. D. Healy and Clinch (2004)	Persons 16–74 years old who are retired[b]

(Continued)

Table 1. (*Continued*).

Indicator	Associated vulnerability factors[a]	Reference	Indicator data set
	Reliant on state pension; spend large proportion of time at home		
Looking after family/home	Precarious or part-time employment; unemployment; dependents and provision of unpaid care; spend large proportion of time at home; lack of control and choice over daily lives	O'Sullivan et al. (2016)	Persons aged 16–74 years looking after family or home[b]
Provision of unpaid care	Precarious or part-time employment; unemployment; dependents and provision of unpaid care; spend large proportion of time at home; lack of control and choice over daily lives	King and Pickard (2013), George, Graham, and Lennard (2013), Norman and Purdam (2013)	Persons providing unpaid care over 20 hours per week[b]
Unemployment	Reliant on low income; unemployment; inability to invest in energy efficiency	J. D. Healy and Clinch (2004), Middlemiss and Gillard (2015)	Persons 16–74 years old who are unemployed[b]
Elementary occupation	Reliant on low income; inability to invest in energy efficiency	Wright (2004)	Persons 16–74 years old in elementary occupations[b]
Proficiency in English	Inability to switch to cheaper tariffs; lack of social relations in/outside home	Bouzarovski (2014)	Household in which not all members over 16 years old speak English[b]
Ethnicity	Reliant on low income; precarious living arrangements; under- or misrepresented in policymaking	Bouzarovski (2014)	Non-British[b]
Full-time student	Reliant on low income; inability to switch to cheaper tariff; inability to invest in energy efficiency measures	J. D. Healy and Clinch (2004), Butler and Sherriff (2017), Petrova (2017)	Full-time students[b]
Underoccupancy	Underoccupancy of the home	Yohanis et al. (2008), Kwon and Jang (2017)	Occupancy rating of +1 bedrooms[b]
Shared property	Inability to invest in energy-efficiency measures; limited availability of energy-efficiency measures; reduced autonomy over energy services	Cauvain and Bouzarovski (2016), Butler and Sherriff (2017)	Shared property[b]
Large household size	Large household size	J. D. Healy and Clinch (2004), Yohanis et al. (2008)	Household size of 6+ persons[b]
Private renting	Inability to switch to cheaper tariff; limited availability of efficiency measures; inability to invest in energy efficiency; lack of housing rights; precarious living arrangements; unaffordability of owner occupancy; under- or misrepresentation in policy; reduced autonomy over energy services	Boardman (2012), G. Walker and Day (2012), Ambrose (2015), Middlemiss and Gillard (2015)	Household that is privately rented[b]
No central heating		Burholt and Windle (2006), Boardman (2013)	Household without central heating[b]

(*Continued*)

Table 1. (*Continued*).

Indicator	Associated vulnerability factors[a]	Reference	Indicator data set
	Inability to access appropriate fuel types; inefficient energy conversion by appliances		
No access to gas network	Inability to access appropriate fuel types; inability to switch to cheaper tariff	Wright (2004), Baker, White, and Preston (2008), Roberts, Vera-Toscano, and Phimister (2015)	Household without access to gas[b]
Energy-inefficient property	Energy-inefficient property	G. Walker (2008), Yohanis et al. (2008), Stockton and Campbell (2011), Dowson et al. (2012), Rudge (2012), Boardman (2013)	Household with EPC ratings F and G[c]
Climatic exposure	Low outdoor temperature	Liddell and Morris (2010), Rudge (2012), Santamouris and Kolokotsa (2015)	Average daily winter temperature[d]

Note: EPC = Energy Performance Certificate.
[a]Extracted from Robinson et al. (2018).
[b]Office for National Statistics (2012b).
[c]Department for Energy and Climate Change (2015).
[d]Met Office (2012).

2015). The index is made up of sociospatial vulnerability factors to represent the characteristics of a household that either enhance or reduce their capacity to resist a loss of well-being and indicator data sets that represent each vulnerability factor and provide measurable information (Table 1). The vulnerability factors and indicator data sets are based on an extensive literature review of energy poverty research over the last three decades, primarily in the Global North. Proxy data sets represent vulnerability factors for which there is not a direct indicator data set, and more than one indicator data set can be associated with a vulnerability factor.

The chosen data sets are available at the Lower Super Output Area (LSOA) scale, a neighborhood boundary that represents between 400 and 1,200 households (Office for National Statistics [ONS] 2012a). Although these boundaries are associated with considerable challenges regarding their spatial resolution and the introduction of statistical bias due to the modifiable areal unit problem (Openshaw 1984), for the majority of indicator data sets this is the highest resolution available. Within each neighborhood, households are the primary unit of analysis, reflecting the shift within research that seeks to understand what shapes vulnerability to energy poverty "away from a concern with individuals to an appreciation of 'the social'—families, communities, municipalities" (Hall, Hards, and Bulkeley 2013, 417).

The majority of indicator data sets were drawn from the 2011 Census Neighbourhood Statistics, the most complete source of information about the population available that facilitates comparisons between small areas and minority populations (ONS 2012b). Two indicator data sets were derived from other sources. First, a data set representing climatic exposure was obtained from the Met Office (2012). Climate projections available in areas of 5 km were transformed into LSOA boundaries. Second, data about the Energy Performance Certificate (EPC) rating for buildings were obtained from DECC (2015) to represent energy efficiency.

It is worth noting that not all households represented by the indicator data sets will be vulnerable; rather, the characteristics are likely to enhance vulnerability when combined with other factors. Mould and Baker (2017) demonstrated how multiple factors can be instrumental in exacerbating household vulnerabilities; for example, pensioners often live alone or have a disability or illness. There are also aspects of vulnerability that indicator data sets are unable to represent explicitly; for example, those associated with mental health and gender. Although some aspects of these vulnerabilities are reflected implicitly in the index due to interrelations with other vulnerability factors, they are poorly understood with respect to energy poverty and lack representative neighborhood-scale data sets. Finally, although the index is intended to be applicable to different

Table 2. Comparing PCA and GWPCA

	Analysis	Output	Purpose	Mapped boundaries
PCA	Global (England)	One set of principal components and loadings for whole study area	Used to calculate the importance of nationally determined aspects of vulnerability between neighborhoods	LSOA polygons
GWPCA	Local (LSOA)	A set of principal components and loadings for each small area that vary according to the importance of vulnerability factors in neighboring areas	Used to understand the factors of importance in determining localized vulnerability in each neighborhood	LSOA PWC

Note: PCA = principal component analysis; GWPCA = geographically weighted principal component analysis; LSOA = Lower Super Output Area; PWC = population-weighted centroid.

national contexts and geographical scales, not all vulnerability factors will be relevant to every geographical context, especially those related to welfare provision or specific policy mechanisms.

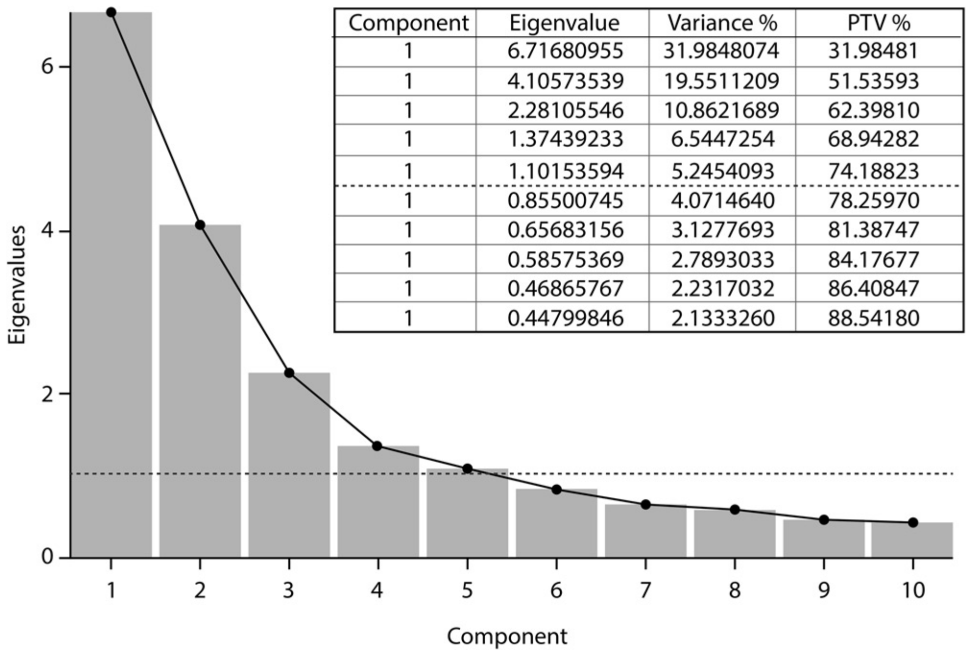
Method: Global PCA and Local GWPCA

PCA reduces a large multivariate set of vulnerability factors into a reduced number of principal components, retaining key statistical information and spatial patterns (Jolliffe 1986). The components have loading values associated with each of the vulnerability indicators in the input data set. Loadings tell us about the type (negative or positive) and strength of the relationship between an indicator and a principal component, providing information about the patterns of vulnerability within the data set that each component is likely to represent. PCA is a global data reduction technique, producing one set of components for the whole data set (in our case for the whole of England). These global component loadings can be mapped to provide an understanding of the spatial distribution of the vulnerability represented by each principal component and the locales in which vulnerability is likely to be enhanced as a result. The loadings are spatially stationary, however, providing what Openshaw (1984) described as "whole-map statistics," without any adaptation to account for spatial effects (Lloyd 2010; Harris, Brunsdon, and Charlton 2011; Demšar et al. 2013).

More recently, a local geographically weighted form of PCA has been developed to better account for these spatial effects (Lloyd 2010; Harris, Brunsdon, and Charlton 2011; Demšar et al. 2013; Gollini et al. 2014; Lu et al. 2014). Applying a local moving window weighting technique, GWPCA generates a localized PCA model for each unit of analysis (in this case each LSOA), producing a new set of components and loadings for each. When mapped, the output can first evaluate how data dimensionality varies spatially and, second, how the original indicators influence each spatially varying component.

Prior to the PCA and GWPCA, indicator data sets were normalized using fractional rank followed by an inverse distance normalization (Hincks et al. 2017). Normalized data sets were then standardized using z scores, defined as the number of standard deviations the data point is from the mean value. In this instance, a high, positive z score is indicative of high vulnerability, whereas a negative z score is indicative of low vulnerability. The normalized and standardized vulnerability indicators were then input into PCA and GWPCA.

In the global PCA, LSOAs are represented by polygons that join to make a continuous surface when mapped. For the local GWPCA, LSOAs are represented by population weighted centroids (PWCs), reference points derived from the spatial distribution of the population. The differences between the PCA and GWPCA are summarized in Table 2. PCA is carried out in R (2.4.1) primarily using the packages *FactoMineR* (Le, Josse, and Husson 2008) and *factoextra* (Kassambara and Mundt 2017). Following the global analysis, GWPCA is



Component	Eigenvalue	Variance %	PTV %
1	6.71680955	31.9848074	31.98481
1	4.10573539	19.5511209	51.53593
1	2.28105546	10.8621689	62.39810
1	1.37439233	6.5447254	68.94282
1	1.10153594	5.2454093	74.18823
1	0.85500745	4.0714640	78.25970
1	0.65683156	3.1277693	81.38747
1	0.58575369	2.7893033	84.17677
1	0.46865767	2.2317032	86.40847
1	0.44799846	2.1333260	88.54180

Figure 2. Eigenvalues for components. PTV = percentage of total variance.

completed using the package *GWModel* (Gollini et al. 2014). To ensure that this article is accessible to a range of audiences, we have opted to exclude the statistical equations associated with the analyses, which are extensive. For a comprehensive overview of the statistical underpinning, see Harris, Brunsdon, and Charlton (2011). In the remainder of this section the global PCA and local GWPCA models are specified.

Specifying the Global PCA Model

The global PCA model is specified with outputs from the analysis. Initially, the global PCA produces as many components as there are indicators, in this instance twenty-one, and their eigenvalues can be used to determine their relative importance (Figure 2). Five components have an eigenvalue of above one and are retained for further diagnostic tests. The Cos. 2 values provide an estimate of the quality of the representation of each vulnerability indicator using each component, suggesting that only components one, two, and three should be retained (Figure 3). The percentage of total variance (PTV) explains how much of the variance in the indicators is explained by the three retained global components, with a PTV of 62.4 percent that is recognized as significant in an analysis of this kind (Hair et al. 1998).

Specifying the Local GWPCA Model

GWPCA requires more information prior to modeling compared to its global counterpart (Harris, Brunsdon, and Charlton 2011). First, the number of principal components must be defined a priori. Second, because the analysis is geographically weighted, a suitable bandwidth must also be determined. The bandwidth is the radius around each neighborhood (represented by a PWC for the geographically weighted analysis) within which the surrounding areas will contribute to the analysis.

The bandwidth for the GWPCA is found automatically using a cross-validation (CV) approach (Harris, Brunsdon, and Charlton 2011). A "leave-one-out" CV score is computed for all possible bandwidths, with the optimal bandwidth relating to the smallest CV score found (Gollini et al. 2014). Here, an adaptive (number of nearest neighbors) bandwidth is selected over a fixed (distance) bandwidth, to allow for a smaller bandwidth around LSOAs in areas where data are denser, primarily urban areas and a larger bandwidth in areas in which LSOAs are sparser, typically in rural areas. An optimal adaptive bandwidth of 1,052 for four components is chosen, similar to the bandwidth determined by Robinson, Bouzarovski, and Lindley (2018), who used geographically weighted regression to examine energy poverty indicators for the same study area.

Having determined a suitable number of retained components and bandwidth, it is possible to assess

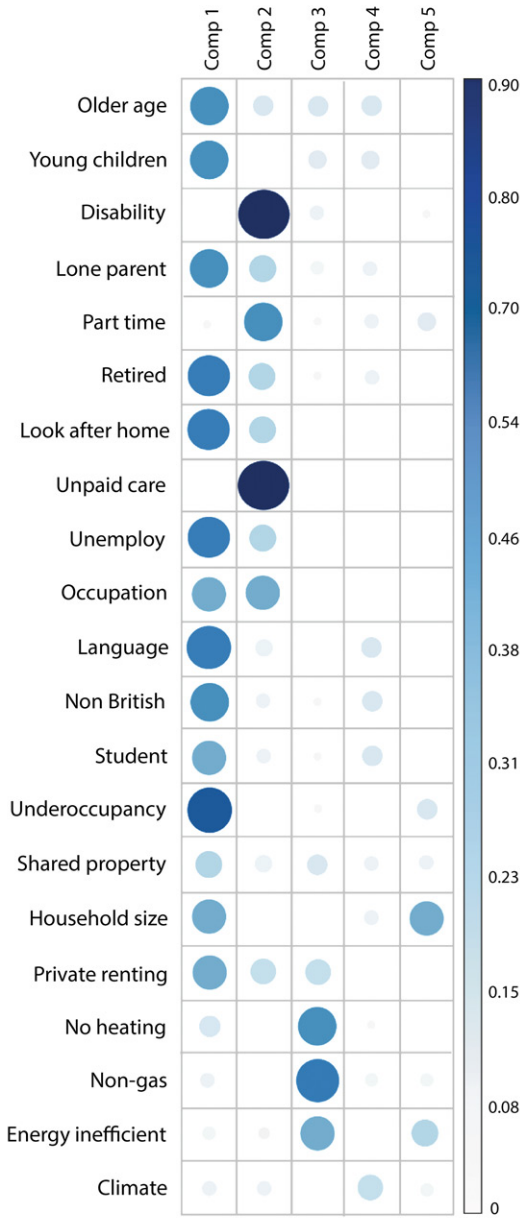
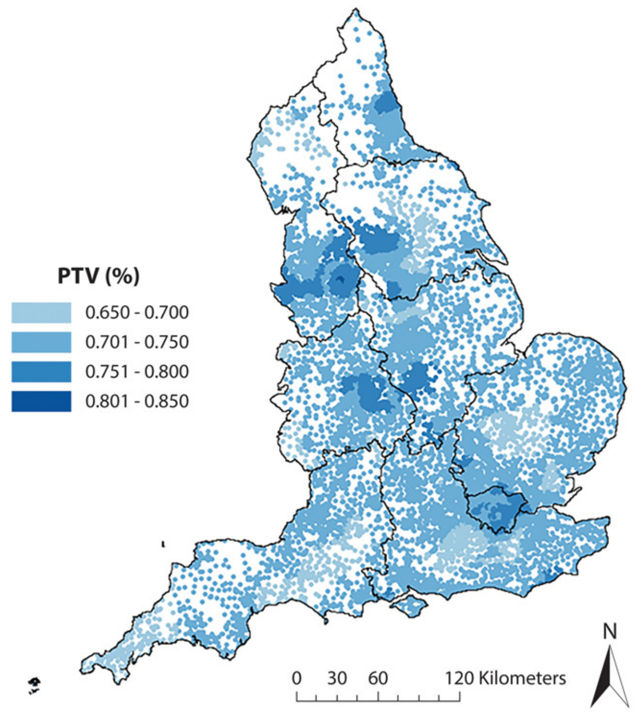


Figure 3. Cos. 2 values for components. (Color figure available online.)

how the data dimensionality varies spatially, to evaluate whether the proportion of variance that is accounted for in the GWPCA model is an improvement on the global analysis. In the absence of a Monte Carlo test (Lu et al. 2014) that could not be carried out owing to the large number of LSOAs within the data set and the size of the resultant matrix, the local PTV values explain how much variance is explained by the four components for each LSOA (Figure 4). The mapped PTV scores were higher than the global PTV score of 62.4 percent, exceeding 65 percent in all LSOAs. A clear



Min	1st Quar.	Median	Mean	3rd Quar.	Max
0.6590	0.7185	0.737	0.7353	0.7516	0.8035

Figure 4. Local PTV explained by the four components retained for each Lower Super Output Area. PTV = percentage of total variance. (Color figure available online.)

spatial variation is evident within the PTV, with local values exceeding 75 percent, concentrating in large urban conurbations across England. A geographically weighted local analysis therefore explains more about the variance in data between LSOAs than a global analysis alone.

The Sociospatial Distribution of Vulnerability to Energy Poverty

Global PCA: The Manifestation of Nationally Determined Vulnerability Factors in Neighborhoods

As outlined in the model specification, the global PCA yields three components, each with a distinct geographical distribution. The loadings of the vulnerability indicators on these finalized components provide information about the type of vulnerability a component is likely to represent (Figure 5 and Table 3). Each component has the potential to represent two aspects of vulnerability, because indicators can load positively and negatively on the components.

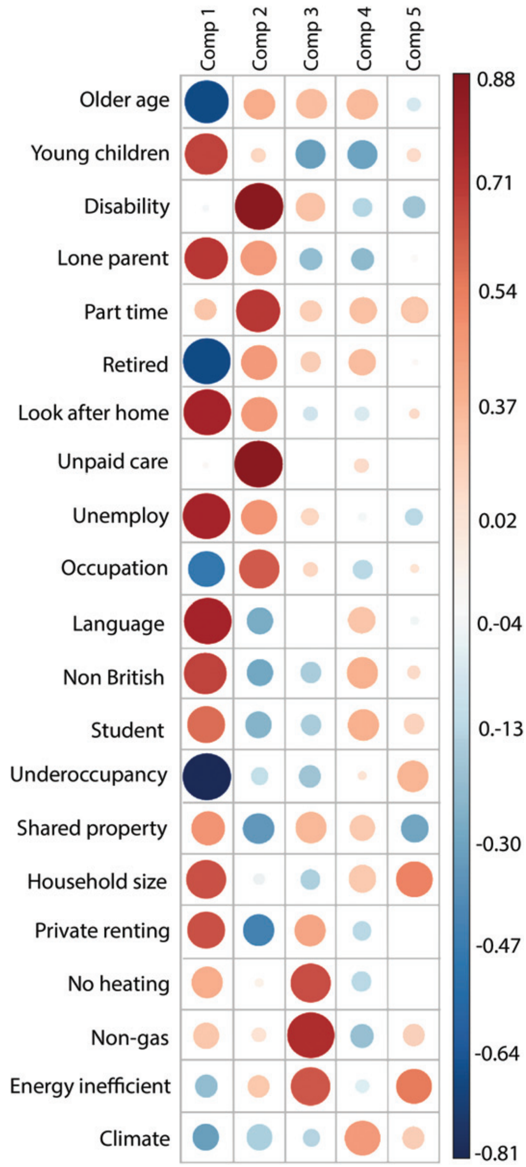


Figure 5. Loading of vulnerability indicators on final components. Red circles indicate a positive loading and blue a negative loading of the indicator on the component. The size of the circle indicates the strength of the loading.

The loadings on the three components for each LSOA are then mapped in Figures 6 through 8. The first component has strong positive association with precarious and transient families but a strong inverse relationship with retirement and older age groups. The second component has a strong positive relationship with disability, illness, and the provision of care. The third component has a positive relationship with the energy efficiency and availability of networked and domestic energy infrastructures.

Component 1: Precarious and Transient Households and Families (+) and Retirement and Older Age (–). Component 1 accounts for 32 percent of the PTV and has a strong positive association with precarious and transient households and families. This includes families with young children (Healy and Clinch 2004), requiring parents to stay at home, especially lone parents (Gingerbread 2013). This strong positive relationship acknowledges the lack of financial security among these families that makes them more likely to be unable to afford sufficient energy services or to invest in energy efficiency. Additionally, the component captures vulnerability in households with precarious living arrangements, including tenants in private or shared properties, in which energy usage and energy efficiency improvements are often difficult to negotiate with a landlord or other tenants (Ambrose 2015; Cauvain and Bouzarovski 2016). The vulnerability of transient groups likely to rely on this sector is therefore recognized, including students (Petrova 2017) and ethnic minorities (Reames 2016). Strong positive vulnerability according to component 1 is spatially concentrated in large urban conurbations across England (Figure 6). Here, transient populations in search of employment are higher, and precarity with respect to income and housing is often most keenly felt (Petrova 2017). This is fueled in part by the unaffordability of owner occupancy in many city regions, especially London, a product of housing policies that have facilitated the privatization of social housing (Forrest and Murie 1988). The results reflect a trend over the last decade of poverty increases among in-work households and in privately rented accommodation (Tinson et al. 2016).

Component 1 also highlights vulnerability associated with retirement and older age, indicators that are negatively associated with the component. This highlights enhanced vulnerability due to a greater physiological need for heat during old age (Ormandy and Ezratty 2012) and enhanced exposure to low indoor temperatures after spending large amounts of time at home during the day (Chard and Walker 2016). In contrast to the transience and precarity that loads positively on component 1, the housing arrangements of those who are older tend to be characterized by greater stability and owner occupancy. This is emphasized by the underoccupancy indicator, which is negatively associated with the component and is common among older people

Table 3. Loading of vulnerability indicators on three finalized components

Vulnerability indicator	Component 1	Component 2	Component 3
Older age	−0.66974476	0.39066855	0.336600163
Young children	0.68614596	0.09628259	−0.327974375
Disability or illness	0.02966585	0.85569704	0.268080151
Lone parent	0.69059916	0.48484296	−0.225889354
Part-time employment	0.18494340	0.68758001	0.181038714
Retired	−0.73320781	0.49332585	0.199179628
Looking after family or home	0.74045834	0.45870279	−0.090305170
Unpaid carer	−0.01822329	0.87720818	−0.006773906
Unemployed	0.73139452	0.47549380	0.124712951
Elementary occupation	0.55024957	0.61081327	0.082119529
Proficiency in English	0.77362949	−0.28894229	0.005503815
Non-British	0.72177996	−0.28639029	−0.163222807
Full-time student	0.58122962	−0.26224797	−0.153850654
Underoccupancy	−0.80537451	−0.11190036	−0.196867580
Shared property	0.43841818	−0.34117096	0.365473243
Large household size	0.60015844	0.06000823	−0.166196227
Private renting	0.57746609	−0.43557550	0.444935303
No central heating	0.39093823	−0.05685681	0.653390375
No gas network access	0.27555613	−0.10340829	0.747411284
Energy-inefficient property	−0.22269965	−0.21440893	0.615789552
Climatic exposure	−0.30228369	0.25475906	−0.146125700

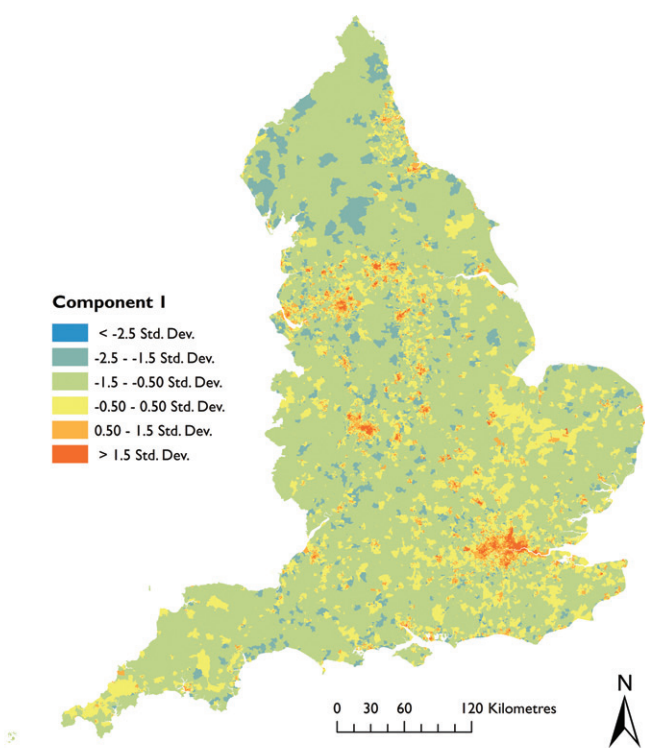


Figure 6. Component 1: Precarious and transient households and families (+) and retirement and older age (–). Red indicates areas of relatively strong vulnerability using positive loadings of indicators and blue indicates areas of strong vulnerability according to negative loadings of indicators. Data extracted from Office for National Statistics (2012a, 2012b).

living in a large property that was formerly the family home (J. D. Healy and Clinch 2004; Kwon and Jang 2017). Underoccupancy increases the amount of space that a household must pay to heat, a burden that might be significant for those reliant on support from the state in older age (Wright 2004; Burholt and Windle 2006; O'Neill, Jinks, and Squire 2006). Enhanced vulnerability in relation to older age and retirement tends to manifest spatially in relatively remote, rural areas where people are more likely to retire and the population tends to be older.

Component 2: Disability, Illness, and the Dynamics of Unpaid Caring Roles (+). Component 2 accounts for 19.6 percent of the PTV and has a strong positive relationship with disability, long-term illness, and the provision of unpaid care. The component represents how disability and illness can increase a person's physiological need for warmth and other energy services and the enhanced vulnerability to energy poverty among these groups due to reduced employment opportunities and likely lower incomes (Snell, Bevan, and Thomson 2015; Gillard, Snell, and Bevan 2017). Additionally, the component captures vulnerability associated with providing unpaid care (George, Graham, and Lennard 2013), recognizing the likely reduction in a carer's capacity to participate in paid employment (King and Pickard

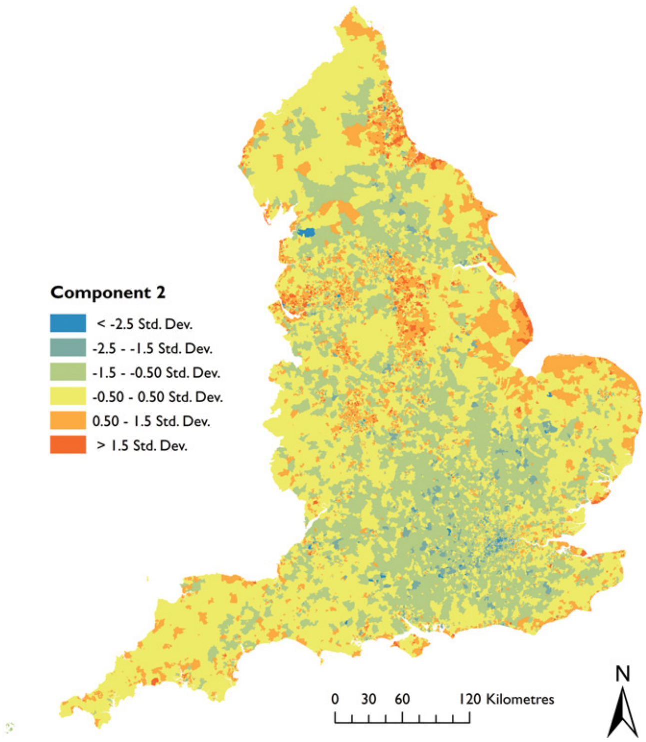


Figure 7. Component 2: Disability, illness, and the dynamics of unpaid caring roles (+) Data extracted from Office of National Statistics (2012a, 2012b). (Color figure available online.)

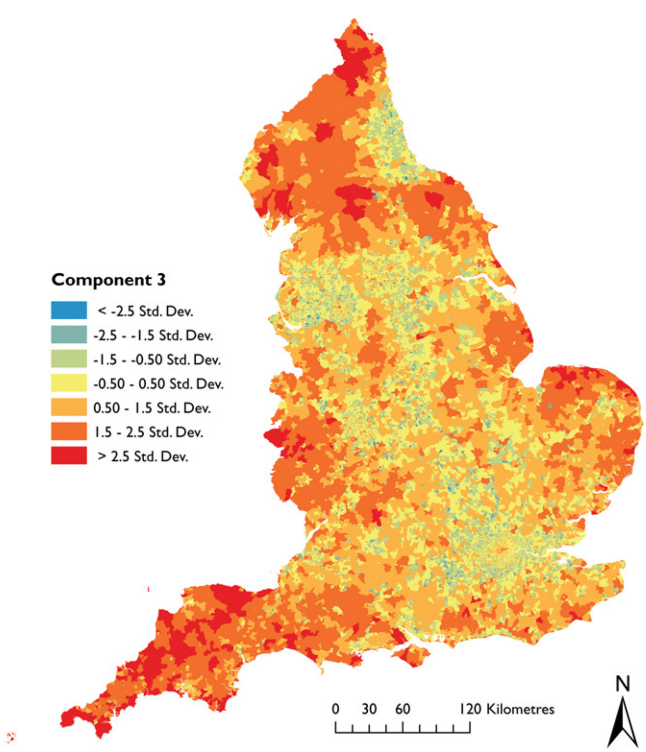


Figure 8. Component 3: Efficient and appropriate domestic and networked infrastructure (+) Data extracted from Office for National Statistics (2012a, 2012b). (Color figure available online.)

2013). The component also draws attention to how people who require support and people who provide care are likely to spend greater amounts of time in the home, resulting in a higher exposure to lower indoor temperatures (George, Graham, and Lennard 2013). Spatially, the component highlights vulnerability in northern city regions that have experienced industrial decline and subsequent income and employment deprivation (Figure 7). Enhanced vulnerability is also apparent in many coastal communities characterized by a high prevalence of disability and illness among an older population and by entrenched income deprivation (Fernández-Bilbao 2011).

Component 3: Efficient and Appropriate Networked and Domestic Energy Infrastructure (+). The third component accounts for 10.9 percent of the PTV and has a positive association with the availability of appropriate and efficient networked and domestic energy infrastructures. The energy-inefficient properties indicator is strongly related to the component. In addition, there is a strong positive relationship with appropriate networked infrastructures, including a lack of access to the gas network that leaves households reliant on more expensive fuel types (Liddell et al. 2012) and domestic infrastructures, including being without central heating (G. Walker, Simcock, and Day 2016). With the exception of pockets of inner-city areas that are without access to the gas network or have a high concentration of low-quality, energy-inefficient, terraced housing, vulnerability is spatially concentrated in rural areas to the north, southwest, and east of England and along the Welsh borders (Figure 8). Here households are likely to be off the gas grid due to their remote geographical location, leaving them reliant on expensive oil for heating (Liddell et al. 2012).

Local GWPCA: Vulnerability Factors Determined by Interaction with Neighboring Locales

Unlike its global counterpart, GWPCA yields a set of components and loadings for each LSOA. Subsequently, a high volume of data is generated for each component that can be difficult to visualize, in this instance twenty-one sets of component loadings for each of the 32,844 LSOAs. The vulnerability indicators with the greatest absolute loading on the components are mapped categorically, what Gollini et al. (2014) termed the "winning variable" for each component. It is worth remembering that the

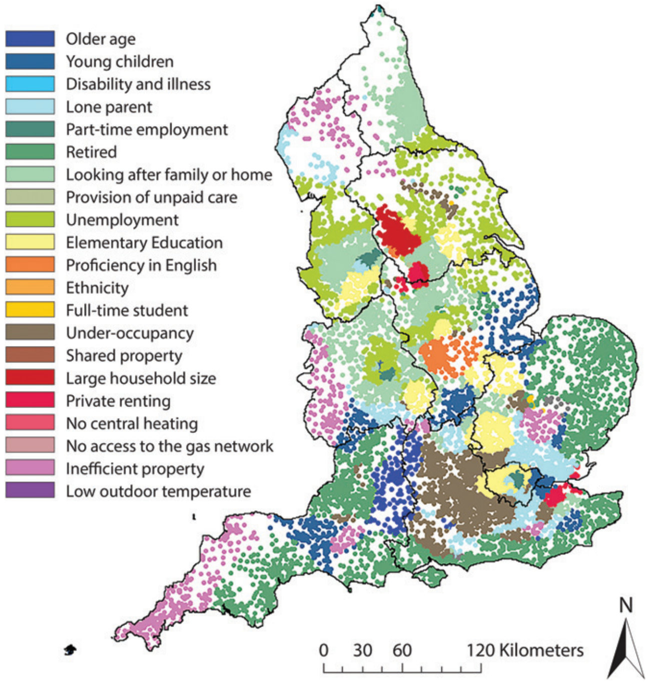


Figure 9. Vulnerability indicators with most positive or negative loading on the first geographically weighted component.

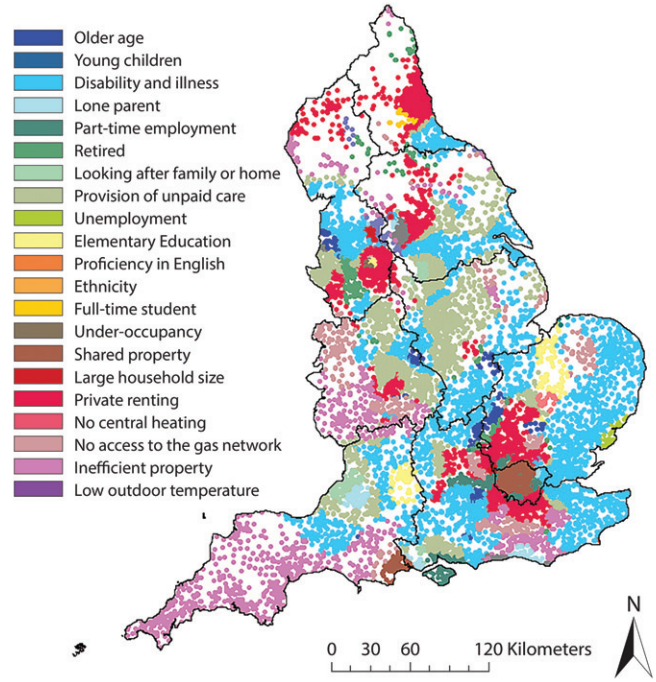


Figure 10. Vulnerability indicators with most positive or negative loading on the second geographically weighted component.

indicators mapped are those that load either most positively or most negatively on to the component. Figures 9 and 10 allow us to visualize which indicators are core to a particular place; therefore, they are likely to play a substantial role in each location when we conceptualize vulnerability based on localized relationships.

Spatial Heterogeneity: Subverting Traditional Deprivation Geographies. Most striking when evaluating these GWPCA outputs is the wide range of indicators that are of greatest importance locally in enhancing vulnerability to energy poverty across England. For the first component (Figure 9) these range from unemployment in swathes of the northwest and northeast, areas of historical industrial decline (Keeble 1978), to energy-inefficient properties in the southwest and the Welsh borders, rural areas in which the housing stock is typified by energy-inefficient, solid-walled properties (Dowson et al. 2012). Similarly, for the second GWPCA component (Figure 10), the indicators that make the greatest contribution toward vulnerability vary from private renters in the suburbs of major urban conurbations, neighborhoods characterized by high levels of housing precarity, to disability, illness, and unpaid care in both rural and urban areas across the country, with the exception of London.

The local analysis therefore highlights how localized vulnerability to energy poverty is multidimensional and spatially heterogeneous. Additionally, it demonstrates how poverty arising from insufficient domestic energy services does not conform to the typical geographies associated with poverty and deprivation more widely. Mapping of localized vulnerability to energy poverty destabilizes common geographical configurations of the urban–rural divide (Department for Communities and Local Government [DCLG] 2015) and the north–south divide (Martin 1988), instead emphasizing the tendency of vulnerability to energy poverty to be highly regionalized and locally specific.

Comparing Global and Local Analyses: Overlapping and Overlooked Vulnerabilities. A comparison of the global and local analyses also provides information about, first, the vulnerabilities that the global analysis represents well and, second, the localized vulnerabilities that the global analysis is likely to underrepresent or obscure.

In some regions, a considerable overlap can be identified between the indicators of greatest importance in the local GWPCA and the sociospatial distribution of components derived from the global PCA. For example, unemployment is the strongest indicator of vulnerability for the first GWPCA component in urban conurbations in the north and the Midlands, corresponding with the spatial distribution of component 1 in the global analysis. This overlap is also recognized in much of the rural south coast and the east of England, where the strongest indicator for the first GWPCA component is retirement, reflecting the strong negative vulnerability according to component 1 in the global PCA. In selected areas a geographically weighted analysis also provides greater detail about the specificities of the global components. For example, the city of Leicester has a strong positive vulnerability according to component 1 of the global analysis, concerned with precarious and transient families. The GWPCA provides greater specificity about the households that are likely to be vulnerable in this area, recognizing the substantial contribution of proficiency in English to vulnerability in one of the most ethnically diverse cities in England (ONS 2012b).

Despite these overlaps, the GWPCA also highlights areas for which the relative strength of the global components does not reflect the indicators that play the most significant role in determining localized vulnerability. For example, for component 1 of the GWPCA there are LSOAs in which a property's energy efficiency is the most important indicator in determining vulnerability; for example, in the southwest of England. In the global analysis, however, energy efficiency is represented by the third component, which only accounts for 10 percent of PTV in the data set. This suggests that a global analysis is likely to underestimate the relative importance of important aspects of vulnerability in some localities.

Finally, the GWPCA recognizes vulnerabilities that are integral to vulnerability in some LSOAs that the global components fail to recognize. For example, the shared property indicator is only weakly associated with the three global components; however, according to the second GWPCA component in central London, shared properties are a defining feature of vulnerability to energy poverty. Cauvain and Bouzarovski (2016) described how energy vulnerability in shared, multiple-occupancy properties in the United Kingdom is "a problem that policy forgot" (8). A geographically weighted assessment of vulnerability can therefore be useful in drawing attention to vulnerabilities commonly overlooked or hidden from policymakers.

Concluding Remarks

The aims set out at the beginning of the article invite reflections on the sociospatial distribution of vulnerabilities that enhance energy poverty and the applicability of spatially constituted methodologies, specifically GWPCA, to understanding sociospatial vulnerabilities.

The global PCA yields three components that represent four vulnerability facets for the whole of England, each with a distinct geographical distribution. It reaffirms the importance of vulnerabilities that are well established in research, including older age, disability and illness, and energy efficiency, whilst drawing attention to less well-understood vulnerabilities associated with precarious and transient households, vulnerabilities that are likely to have become starker during an era of austerity. These global components are useful in highlighting broad vulnerabilities and considering their relative importance between neighborhoods. They also draw attention to the structural factors that shape sociospatial patterns of vulnerability, including uneven economic growth, falling real incomes, unequal housing markets, inadequate welfare support, the rising cost of living, and a lack of recognition or voice, among others.

These global components and their spatial distribution can inform the future trajectory of energy poverty research, allowing for identification of nationally important aspects of vulnerability and different locations in which these are likely to manifest that could benefit from in-depth qualitative research. The results also have implications for policymaking, suggesting the need for an energy poverty narrative in England beyond the existing concern with warmth for the elderly. Currently in Britain, an estimated £2 billion to 3 billion is spent on a universal, non-means-tested payment to pensioners to help cover the cost of heating during the winter months. This represents the bulk of spending on energy poverty alleviation. Although highlighting that this is one significant aspect of vulnerability, our analysis suggests that it is only part of the problem (conferring with G. Walker and Day 2012). The global components could be used to focus policy mechanisms to alleviate certain aspects of vulnerability including, for example, more equitable financial mechanisms related to energy for component 1, policies tailored toward individual energy-related needs for component 2, or extensive and equitable energy-efficiency schemes in relation to component 3.

In contrast, the local GWPCA reveals a greater spatial heterogeneity in vulnerability than its global counterpart, which has a tendency to universalize vulnerability based on common spatial configurations. The local analysis recognizes how energy poverty does not conform to the typical geographies associated with deprivation more widely, including the urban–rural and north–south divides, instead emphasizing the tendency of vulnerability to energy poverty to be highly regionalized and locally specific. It succeeds in making visible a diverse range of geographies associated with vulnerability to energy poverty, including those that are often "hidden" when policymakers and practitioners tackle this form of deprivation (Buzar 2007). Knowledge of the localized heterogeneity of vulnerability to energy poverty could be productively utilized by policymakers or practitioners, providing an improved understanding of the challenges that typify particular locales. Such local knowledge is likely to be beneficial in comparison to existing understandings of who is most vulnerable that are largely derived from narrow national-scale policies and indicators.

One caveat of the geographically weighted approach relates to mapping of the outputs. It is not possible to map the relative vulnerability that the global PCA results and, indeed, other assessments of deprivation (DCLG 2015) and vulnerability (Cutter, Boruff, and Shirley 2003) tend to use. Such a relative understanding of vulnerability and disadvantage is important in a context in which high levels of inequality exist and an inability to participate meaningfully in the society in which one lives is the distinguishing feature of poverty and vulnerability (Townsend 1987; Boardman 1991; Buzar 2007). Despite this, the GWPCA results can be useful in verifying global vulnerability assessments, understanding challenges of energy poverty in a specific local authority or city region, and informing neighborhood-scale targeting of the energy poor.

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