# Creating an energy deprivation classification at small areas in England and Wales

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**Summary**

In response to the increasing energy crisis, this study concentrated on the problems of energy deprivation in small areas of England and Wales. We create an energy deprivation classification from multiple measurements within four domains based on the extensive literature on vulnerability to energy poverty. By applying a commonly used k-means clustering method, we discover nationwide spatial disparities and distinctive characteristics of energy deprivation at fine spatial units.

**KEYWORDS:** spatial inequality, energy deprivation, geodemographics, urban analytics

## 1. Introduction

Energy poverty is commonly used to describe the problems of domestic energy deprivation (Bouzarovski & Petrova, 2015), which can be defined as the lack of access to energy services, such as heating and lighting, that are adequate, affordable, reliable, high-quality, safe and environmentally friendly (Reddy et al., 2000; González-Eguino, 2015). Energy deprivation has a wide range of negative effects on health and well-being, social relations, education opportunities and economic development (Bouzarovski & Petrova, 2015; Liddell & Morris, 2010), and may also hinder the accomplishment of targeted policy on net-zero greenhouse gas emissions by 2050 for the UK government (BEIS, 2021).

To address these issues, understanding spatial distribution and characteristics of energy deprivation is necessary and significant to inform the development of targeted and effective policy and programmatic solutions. Additionally, exploring energy deprivation can give insight into the broader socio-economic and political issues that contribute to it. Within this context, this study aims to create a nationwide energy deprivation classification in small areas to understand the energy poverty issues better and help policymakers' decision-making.

## 2. Data and Methods

Data are identified from multiple datasets, including domestic Energy Performance Certificates (EPCs), Census, Department for Business, Energy & Industrial Strategy (BEIS) and Department for Work and Pensions (DWP) statistics in England and Wales. EPCs are evaluation certificates when the properties are built, sold or rented, which provide essential information about energy efficiency of the buildings since 2008 and are valid for ten years (Gov.UK, n.d.). Census, BEIS and DWP data publish

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official statistics at national, regional and local levels at varying update frequency. All datasets are collated in the most recent years to ensure the temporal effectiveness and representation of the energy classification, providing timely and valuable implications for policymakers.


Figure 1 Domains and measures of energy deprivation[4]

The determination of four domains and relative measures of energy deprivation is primarily based on the extensive review of vulnerability to energy poverty (Bouzarovski & Petrova, 2015; Liddell & Morris, 2010; Petrova, 2018; Robinson et al., 2018, 2019; ONS, 2022; DEFRA, 2022). Each domain contains a list of measures of energy deprivation aggregated in the Census 2021 geography of Lower Super Output Area (LSOAs). These geographic units provide adequate details for identifying local variations while also being large enough to produce reliable estimates (Singleton et al., 2020). Figure 1 provides a summary of 23 measures within four domains of energy deprivation. The 'Energy Efficiency' domain contains information on the inability to change energy efficiency and identified energy inefficient properties. The 'Energy Accessibility' domain measures the accessibility to central heating, different fuel types and prepayment electricity meters. The domain of 'Energy Demand and Service' represents variables that reflect the imbalance between high energy demand and inadequate services, and the domain of 'Financial vulnerability' captures attributes with reliance on vulnerable financial conditions.

[4] The symbol '*' represents measures that are not included for the next energy deprivation classification.

All measurements are transformed into percentages to reduce the effects of the unbalanced size of the population, household and property. Box-cox transformation and Z-scores standardisation are conducted to convert skewed data into normalisation and enable them at the same scale. These methods have been commonly implemented when creating a geodemographic classification (Liu et al., 2021; Singleton et al., 2016), ensuring each measurement's equal contribution and interpretable outputs. Pearson's correlation matrix is then produced to minimise variables that have strong associations (greater than $\pm$0.8), as these can assign a higher weight to a particular phenomenon which negatively affect the classification (Spielman & Singleton, 2015). Figure 2 illustrates the correlation values between each pair of measures numbered by Figure 1, with green and pink colours representing positive and negative relationships. Strong correlations are presented in three pairs: measure 1 and 3, measure 12 and 22, and measure 13 and 23. Therefore, we remove the measures on carbon dioxide emission per square metre, universal credit and state pension accredited to their extremely strong positive associations with one or more others.

| | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 1.00 | | | | | | | | | | | | | | | | | | | | | | |
| **2** | 0.04 | 1.00 | | | | | | | | | | | | | | | | | | | | | |
| **3** | 0.76 | 0.29 | 1.00 | | | | | | | | | | | | | | | | | | | | |
| **4** | 0.46 | 0.09 | 0.50 | 1.00 | | | | | | | | | | | | | | | | | | | |
| **5** | 0.26 | -0.04 | -0.02 | -0.24 | 1.00 | | | | | | | | | | | | | | | | | | |
| **6** | -0.37 | 0.00 | -0.28 | -0.14 | -0.50 | 1.00 | | | | | | | | | | | | | | | | | |
| **7** | 0.00 | -0.26 | 0.10 | 0.54 | -0.45 | -0.03 | 1.00 | | | | | | | | | | | | | | | | |
| **8** | 0.02 | -0.01 | 0.08 | 0.52 | -0.29 | 0.02 | 0.51 | 1.00 | | | | | | | | | | | | | | | |
| **9** | 0.15 | -0.27 | 0.16 | 0.35 | -0.38 | 0.19 | 0.57 | 0.30 | 1.00 | | | | | | | | | | | | | | |
| **10** | -0.43 | 0.32 | -0.06 | -0.01 | -0.46 | 0.14 | 0.15 | 0.13 | 0.00 | 1.00 | | | | | | | | | | | | | |
| **11** | 0.26 | -0.54 | 0.00 | 0.06 | 0.09 | 0.02 | 0.29 | 0.05 | 0.35 | -0.51 | 1.00 | | | | | | | | | | | | |
| **12** | -0.18 | 0.06 | -0.05 | 0.14 | -0.55 | 0.75 | 0.23 | 0.12 | 0.38 | 0.22 | -0.03 | 1.00 | | | | | | | | | | | |
| **13** | 0.28 | 0.18 | 0.20 | -0.26 | 0.55 | -0.36 | -0.54 | -0.29 | -0.37 | -0.24 | -0.03 | -0.49 | 1.00 | | | | | | | | | | |
| **14** | -0.32 | 0.06 | -0.17 | -0.04 | -0.51 | 0.72 | 0.05 | -0.05 | 0.17 | 0.24 | -0.17 | 0.74 | -0.51 | 1.00 | | | | | | | | | |
| **15** | 0.08 | 0.11 | 0.12 | 0.20 | -0.25 | 0.20 | 0.25 | 0.09 | 0.21 | 0.12 | -0.06 | 0.35 | -0.41 | 0.22 | 1.00 | | | | | | | | |
| **16** | 0.29 | 0.18 | 0.14 | -0.20 | 0.71 | -0.65 | -0.59 | -0.40 | -0.55 | -0.28 | -0.19 | -0.68 | 0.66 | -0.52 | -0.44 | 1.00 | | | | | | | |
| **17** | -0.17 | 0.12 | 0.00 | 0.06 | -0.46 | 0.72 | 0.04 | 0.01 | 0.18 | 0.20 | -0.10 | 0.71 | -0.22 | 0.64 | 0.14 | -0.45 | 1.00 | | | | | | |
| **18** | -0.03 | 0.09 | 0.02 | 0.12 | -0.37 | 0.52 | 0.16 | 0.01 | 0.24 | 0.13 | -0.07 | 0.62 | -0.46 | 0.60 | 0.68 | -0.55 | 0.49 | 1.00 | | | | | |
| **19** | 0.02 | 0.07 | -0.06 | -0.24 | 0.38 | -0.59 | -0.47 | -0.26 | -0.45 | -0.02 | -0.29 | -0.56 | 0.09 | -0.30 | -0.22 | 0.62 | -0.52 | -0.37 | 1.00 | | | | |
| **20** | 0.18 | 0.28 | 0.18 | -0.24 | 0.31 | -0.05 | -0.62 | -0.33 | -0.32 | -0.09 | -0.23 | -0.12 | 0.63 | -0.05 | -0.18 | 0.44 | 0.18 | 0.03 | 0.12 | 1.00 | | | |
| **21** | -0.12 | 0.18 | -0.01 | -0.09 | -0.11 | 0.16 | -0.14 | -0.23 | -0.05 | 0.12 | -0.26 | 0.26 | -0.21 | 0.37 | 0.22 | -0.03 | 0.16 | 0.19 | 0.12 | 0.01 | 1.00 | | |
| **22** | -0.21 | 0.01 | -0.02 | 0.21 | -0.63 | 0.71 | 0.39 | 0.18 | 0.41 | 0.28 | -0.05 | 0.87 | -0.58 | 0.76 | 0.37 | -0.75 | 0.77 | 0.68 | -0.60 | -0.16 | 0.25 | 1.00 | |
| **23** | 0.30 | 0.13 | 0.20 | -0.24 | 0.58 | -0.39 | -0.54 | -0.28 | -0.36 | -0.27 | -0.03 | -0.50 | 0.95 | -0.51 | -0.41 | 0.68 | -0.23 | -0.46 | 0.13 | 0.64 | -0.21 | -0.57 | 1.00 |
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** | **17** | **18** | **19** | **20** | **21** | **22** | **23** |

Figure 2 Correlation matrix for final selection of measures

Accordingly, a commonly used k-means clustering is conducted to group all LSOAs in England and Wales. The value of k is determined by Clustergram (Schonlau, 2002), which displays a range of possible k values and the average of their primary component with weight. It is a useful tool to visualise how the data is redistributing itself and how good the splits are. From the illustration of Figure 3, K=5 generates robust results after multiple iterations.

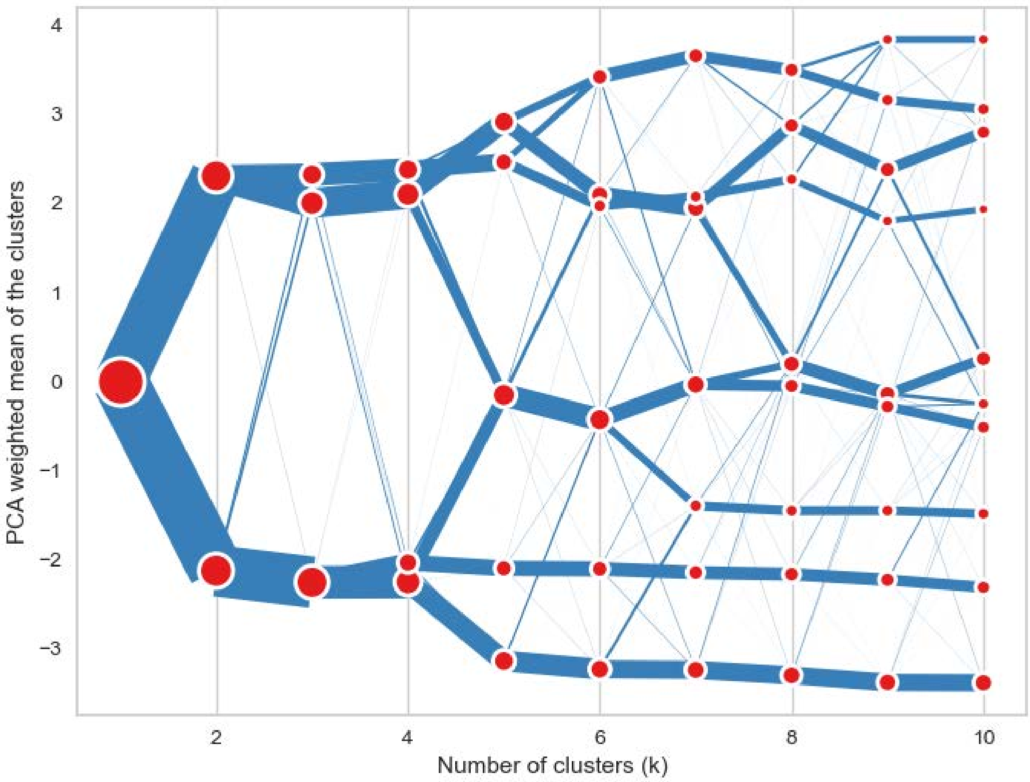


Figure 3 Clustergram for the determination of cluster numbers

## 3. Results and Discussion

Five groups of energy deprivation are produced in LSOAs in England and Wales, with the number of small areas ranging from 5,300 to 9,300 per group. Figure 4 displays the spatial disparities of energy deprivation, and Figure 5 illustrates distinctive profiles for all groups. The Cluster A captures a clear imbalance between high energy demand and low energy services of the most vulnerable urban residents. This category is primarily distributed in the most deprived areas with struggling citizens who have inability to meet their essential energy needs given their lack of housing rights, have health issues or caring responsibilities, live in crowded bedrooms, or have vulnerable financial conditions.

The population of the group B tend to live in historical and cultural areas with an appropriate level of energy in terms of four domains. Almost all measurements are centred around the national average scale except for 'owns with mortgage or loan', implying that residents have reasonable economic conditions to afford properties and are eligible to invest in energy efficiency and access to appropriate fuel types.

The Cluster C primarily aggregated at rural suburbs of small towns and cities. Residents in these areas are more likely to be older adults who live in relatively new detached houses with property ownership and spare bedrooms. They have the greatest energy accessibility, including central heating, gas networks and prepayment electricity meters. Yet, the energy is less environmentally friendly because they tend to have mortgages or loans that may limit their investment in renewable energy.

Areas categorised in the Cluster D have the largest areas while the least number, comprising large quantities of countryside across England and Wales. Compared to other groups, this group has the most ageing population living in detached and relatively old houses using various types of renewable energy rather than mains gas connected to the gas grid. However, the energy is primarily used inefficiently in these areas, probably due to more spare bedrooms in the detached houses.

The last group E is mainly seen in London and central areas of major cities. These areas' properties were largely constructed before 1930 with no central heating, gas network and limited renewable energy. Detached houses rarely appear and private renting and sharing properties are leading living arrangements. Residents from these areas are more economically active while a lack of housing ownership leads to inability to improve energy efficiency or accessibility.

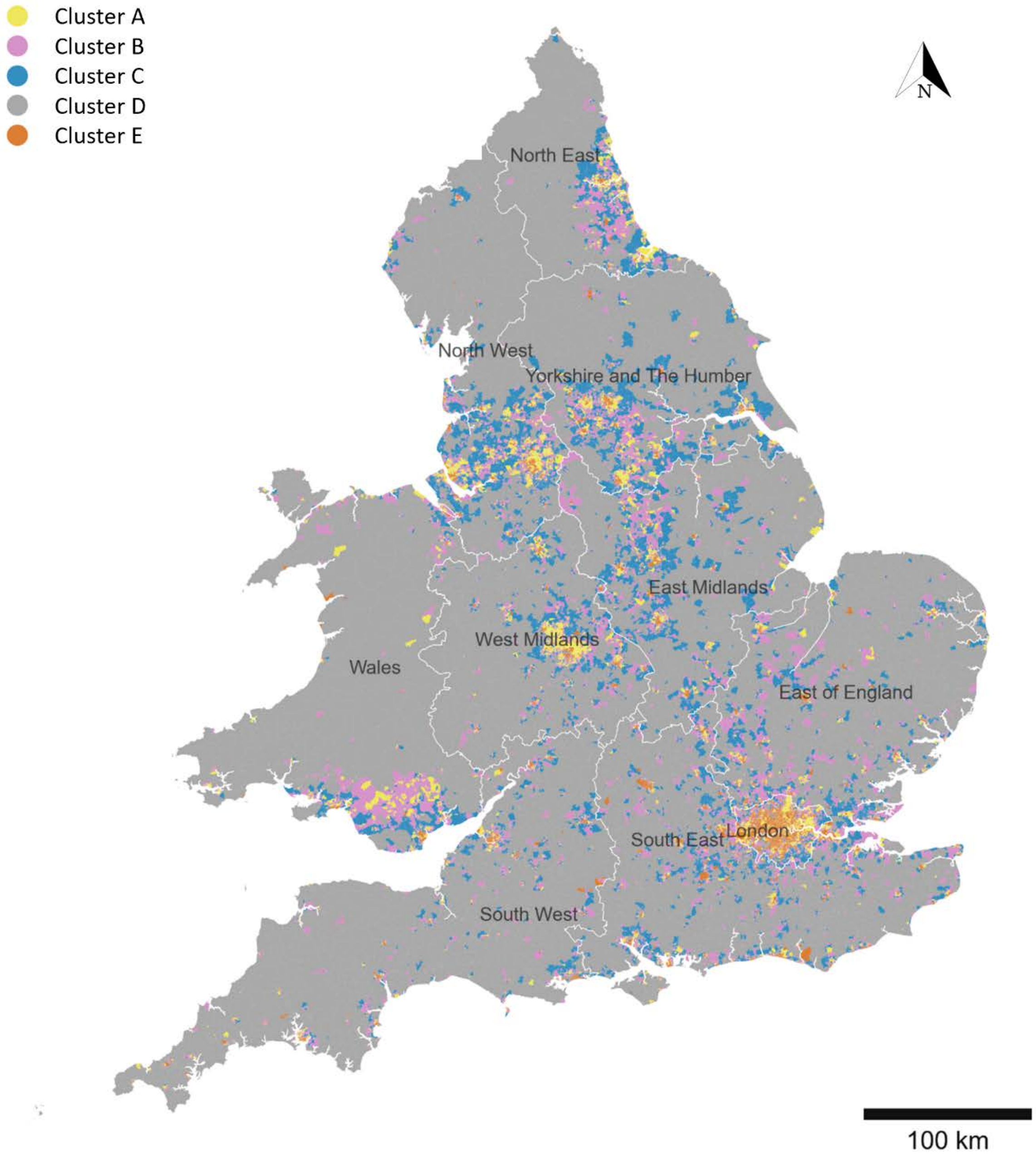


Figure 4 Map of energy deprivation for England and Wales

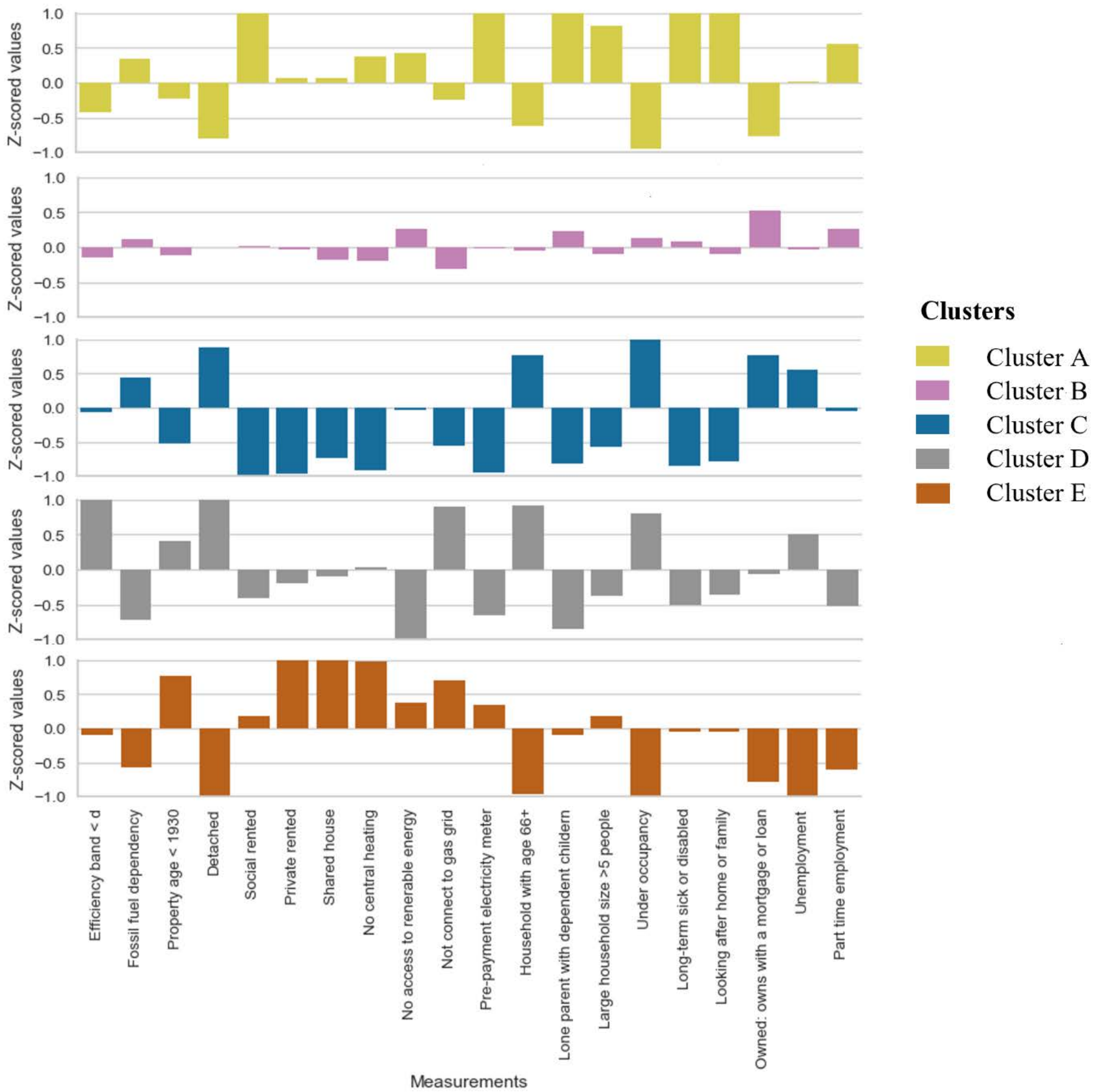


Figure 5 Profiles of each cluster group

## 4. Conclusion

This study creates an energy deprivation classification in small areas in England and Wales based on multiple measurements within four domains, including energy efficiency, energy accessibility, energy demands and services, and financial vulnerability. By clustering the measures at small spatial units, we identified the distributions and characteristics of energy deprivation. Our future work will include more valuable measurements and subdivide the initial categories to profile finer aspects of energy deprivation.

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**Biographies**

Meixu Chen is a postdoctoral research associate of Geographic Data Science Lab and ESRC CDRC at the University of Liverpool. Her research is centred on understanding population and individual activities, behaviours, and dynamics using geographic data science methodologies, particularly interested in residential and human mobility, social sensing, and socio-spatial inequality.

Caitlin Robinson is a research fellow and proleptic lecturer in the School of Geographical Science at University of Bristol. She uses quantitative methods to understand the causes and consequences of different types of spatial inequality across multiple scales, with a particular interest in energy poverty and energy justice.

Alex Singleton is a professor of Geographic Information Science at the University of Liverpool, and Deputy Director of the ESRC CDRC. His research is concerned with how the complexities of individual behaviours manifest spatially and can be represented and understood though a framework of geographic data science.