Gridded-glyphmaps for supporting Geographic Multicriteria Decision Analysis

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Abstract

Integrating human intuition into data-driven decisions is challenging. Multicriteria Decision Analysis (MCDA) provides a structured framework for evaluating multiple criteria but often fails to capture the nuanced preferences of decision-makers. Geovisualisation tools can help understand data, but representing intricate relationships within MCDA models, especially with multivariate data, remains difficult. This study proposes a solution by combining MCDA and geovisualisation strengths using gridded-glyphmaps. This approach enables interactive exploration of multivariate geospatial data, allowing decision-makers to adjust parameter weights in real-time and dynamically assess decision alternatives. We demonstrate this approach's effectiveness through decarbonisation planning scenarios in Cambridge, UK. Our glyphs represent multiple variables' interplay, allowing for flexible criteria weight refinement. Discretising the data into grids reveals patterns and relationships missed by traditional representations like choropleth maps. Our approach demonstrates how gridded-glyphmap visualisation within an MCDA model fosters insights and transparency in decarbonisation planning scenarios.

CCS Concepts

• ***Human-centered computing*** → ***Visualization techniques; Geographic visualization;*** • ***Information systems*** → *Decision support systems;*

1. Introduction

Multicriteria Decision Analysis (MCDA) is a methodology that supports complex decision-making using multiple criteria based on multivariate datasets [ZW76, HY12]. In a geographical context, decisions often require the identification of locations of interest, with criteria being based on multivariate geographical data [MR15]. Essentially, geographical MCDAs produce models that identify locations of interest by weighting multiple spatial variables to different degrees as criteria that may conflict with each other. They are often used for the deployment of green infrastructure. Examples include identifying suitable locations for solar and wind farms [DHE22], siting electric car charging points [GY20, BM23], or evaluating possible scenarios for district heating demand [DSDZ22]. Geographical MCDA can be applied either computationally or visually [MR15]. The former involves capturing the interplay between variables and their contributions to decision making into a formal computational model, using modelling approaches such as Simple Additive Weighting (SAW) [ZW76, Saa08], the Analytical Hierarchical Process (AHP) [Saa08] or Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [OB11]. The latter involves visual interpretation as part of the modelling process [ATS95, CSK*21, RV13]. Geovisualisation can facilitate interaction between geographical space and MCDA criteria and can be effective for helping reveal patterns that would otherwise be hidden to decision makers [JAA01]. Interactive geovisualisation tools support MCDA by allowing analysts to visualize the dynamic effects of modifying decision settings on spatial outputs. This iterative process facilitates the fine-tuning of MCDA settings for more informed decision-making, further emphasised by the analyst's knowledge of the study area [Rin07].

The challenge in representing multiple variables geographically and simultaneously, especially with multiple decision making scenarios, is significant. MCDA results are often presented as multiple univariate choropleth maps that show location suitability [RV13]. While this approach allows decision makers to visually compare location suitability from different alternatives, it does not reveal how the criteria and multivariate data contribute to the modelled outcomes [JAA01]. By depicting how the criteria and multivariate data contribute to the outcomes, we think analysts will be able to better validate the models and choose between alternative scenarios. By coupling the depiction of how the criteria and multivariate data contribute to the model outcomes with the modelling process, we think that analysts will be able to better tune models that provide plausible outcomes and gain insights into the process [MR14].

We tackle this challenge by exploring the use of gridded glyphmaps [Sli18] to depict input multivariate geographical data,

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the weights that define the MCDA model, and the MCDA outputs of location suitability. Gridded-glyphmaps use interactive glyphs and geospatial binning and have been found to be effective in supporting spatial modelling [SRH23]. Within the context of MCDA, each variable in the data ('criterion' space) is reflected in the glyph design encoded within geographic enumeration unit ('decision' space). The aim of this paper is to demonstrate potential for this approach to facilitate decision-making by employing interactive multivariate geospatial visualisation of different scenarios in geographical MCDA. We also consider how this technique can help explore the sensitivity of the criteria to the outcomes. We illustrate the effectiveness of this approach on the case for decarbonisation planning in Cambridge using Simple Additive Weighting (SAW) model. This is demonstrated by our implementation which also compares this approach alongside the more traditional univariate choropleth map for depicting site suitability.

2. Related Work

We build on previous studies on coupling geovisualisation and GIS-based MCDA, in particular how the former facilitate a better understanding of complex MCDA models.

Coupling Geovisualisation and MCDA. Within the computational domain of MCDA, GIS can be used to facilitate informed decision-making on geographical data by combining input and decision maker preferences into geographically defined alternatives [MR15, Mal06]. MCDA allows decisions where multiple criteria are involved that may well conflict. MCDA has different methods to facilitate this, ranging from simple models such as Simple Additive Weighting (SAW), Analytical Hierarchy Process (AHP) or more complex ones such as PROMETHEE (preference ranking organization method for enrichment of evaluations) [KSS*17]. Whilst the inner workings of these models might be apparent for an analyst, the intricacies grow as models become more complex and decision maker preferences conflict [SSB24]. Visualising the components of these models helps identify the interplay between input data and model parameters [ATS95]. Facilitating interactive model parameterisation [AJA00] can allow decision makers to incorporate their own preferences into the modelling process. Other techniques such as Multiple Coordinated Linked Views [ASS*02, JAA01, AA03] have been demonstrated in geographical MCDA contexts [Rin03, RV13, HND*16], where an interactive interface has enabled model parameter manipulation. In such cases, the resulting scenarios are often presented as choropleth maps or tables representing the final score for each geographic unit.

Visualising Multivariate Geospatial Data in geographical MCDA. Coupling geovisualisation with MCDA enables geographic data exploration and facilitates the understanding of complex multivariate data, especially when multiple criteria is involved. Visualising multivariate data on maps is inherently hard, given the limitations of two-dimensional space to effectively represent multiple, often complex, variables simultaneously. While maps excel at displaying geographical data, conveying additional attributes – e.g. socio-economic indicators, environmental variables, or low-carbon technology potentials – can lead to visual clutter and ambiguity. In the context of MCDA, Markieta and Rinner [MR14] depicted multiple input variables by overlaying multiple layers of maps whose transparencies were individually weighed. Seebacher et.al. [SMP*19] used glyphs to model parameters with interactive interface for modifying weights of individual geographic data points in a machine learning model. We build on this work by using gridded glyphmaps [SRH23] to enable multivariate data visualisation and geographic binning of MCDA model, whilst simultaneously facilitating model refinement through interactive adjustment of model parameters. Our gridded glyphmaps not only depict the inner workings of the model, but help explore different scenarios, catering for different decision makers' preferences [ZP04, SRH23].

3. Case study

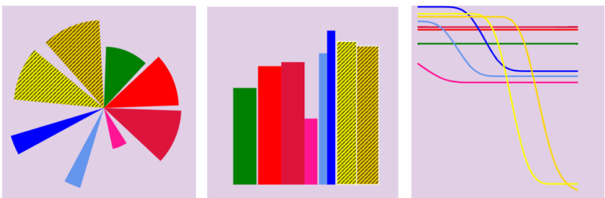
Our case study is based on decarbonisation plans for Cambridge. The goal is to identify areas of Cambridge that show most potential for prioritising decarbonisation strategies. We are working with Advanced Infrastructure Technology Ltd. (AITL) – a green infrastructure consultancy – who are working with Cambridge City Council whose vision for achieving Net Zero by 2030 seeks to balance parameters such as technological solutions, social impacts, and economic burdens over six main objectives. Currently, AITL employs Local Area Energy Planner Plus (LEAP+) platform to forecast which area to prioritise for decarbonisation, given different combinations of the parameters in each scenario using GIS operations between geographic layers. While users are able to adjust which decarbonisation parameters to prioritise, the calculations itself are hidden. Changing the prioritisation in each scenario will require the users to repeat the steps. The resulting calculations are presented as a series of choropleth maps within each administrative boundary, utilising layered approach to visualise different output in each scenario. We use gridded-glyphmaps to enable these functionalities currently missing in the platform.

We use Lower Layer Super Output Area (LSOA) datasets in Cambridge representing opportunities for low-carbon technologies, social impacts and economic burden aims to achieve the objectives. The *annual photovoltaic potential* dataset can guide solar panel installation, reducing carbon emissions. *Number of houses suitable for air and ground source heat pumps* can target energy-efficient heating solutions, reducing energy consumption. *Number of houses with Energy Performance Certificate (EPC) rating higher than E* can identify areas for energy efficiency improvements. *Annual electricity and gas demand* datasets can identify opportunities for energy-saving measures, reducing resource consumption. *The percentage of fuel poverty* and *Index of Multiple Deprivation* [Nat19] datasets can guide assistance programs to ensure equitable access to sustainable energy solutions, enabling Cambridge with the decarbonisation goals while leaving no one behind.

4. Design

To simulate how this approach is able to cater for decision makers' preferences, we developed multiple decarbonisation scenarios for the model. Each scenario has different a different configuration of weights for each parameter, ranging from -1 to 1. In 'Scenario I', we seek to measure renewable energy potentials by focusing on photovoltaic (PV) generation, air source heat pumps and ground source heat pumps, whilst sticking to socio-demographics that are more likely to be able to adopt them. In 'Scenario II', we simulate prioritising energy conservation by highlighting fuel poverty, deprivation and energy consumption parameters. 'Scenario III' seeks to balance out the overall parameters to understand the patterns beyond the final output score. These scenarios involve an implementation of Simple Additive Weighting (SAW) to calculate the MCDA scores. We capture how the change in interactive weighting affects individual parameter and the overall scores within each cell, allowing for fine-tuning the criteria in each scenario.

Figure 1 showcases how we encode the parameters into glyphs. The LSOA level data are resampled into 5×5 km^2 grids to distribute the data evenly across the administrative boundary. We use two main types of glyphs: bar chart and rose chart. These represent the same data in slightly different ways, allowing us to test which is easier to understand in a future study. These glyphs also show how much weight is given to each factor in different scenarios. A third type of glyph, a line chart, tracks how the overall score for each area changes as the weight given to different factors is adjusted. This helps analysts see how important each parameter is to the final scores. Enabling the relative scores will reveal the interplay of parameters in-between the cells. The goal is to help decision-makers understand how the model works by showing how different factors interact within each cell area. We achieve this by using these glyphs alongside a traditional choropleth map that shows the final score within each LSOA boundary.



a. Rose chart b. Bar chart c. Line chart

Figure 1: *"Rose chart" (a) and "bar chart" (b) designs encoding decarbonisation parameters (colour hues), cell's score (bar height and pie radius), weights (bar and pie width), and weights' signs (textured for barriers). "Line charts" (c) records the recent history (x-axis) of adjustments to parameter scores (color hues; y-axis) with the model output score encoded in cell backgrounds similar to the choropleth map.*

5. Discussion

Glyphs and Interactivity Designs: The dashboard in Figure 2 demonstrates our approach. The gridded-glyphmaps facilitates both overview and detailed view, showing the interplay of multivariate parameters in each cell. We found that coupling interactive geovisualisation with multivariate visualisation of MCDA parameters using gridded-glyphmaps allows decision makers using the platform to: 1) interactively manipulate parameter weights and simultaneously view how it affects the multivariate parameters; 2) delve into the interplay between parameters, and how each parameter affects the final score through the glyphs; 3) get an overview of the nuanced distribution of data across the gridded space, while still providing details on demand to each parameter; 4) get insights into how the model behaves across different cells by visualising the relative scores; and 5) track the historical change of the parameter, allowing for fine-tuning the model.

The rose chart and bar chart shows how different visualisation designs can encode decarbonisation parameters. We found that bar chart's encoding is more visually intricate that in the rose chart, complicating the differentiation between parameters, particularly when dealing with smaller grid sizes. This complexity is also evident for parameters with lesser weights, as their representation through bar width lacks visual prominence.

Multicriteria Data Exploration: We use the gridded-glyphmaps to evaluate the different scenarios for Cambridge's decarbonisation planning. Figure 2 demonstrates how the platform can be used to highlight Scenario I: optimise low-carbon technology and avoid socio-demographic barriers. Adjusting the weights, the gridded-glyphmap displays each parameter's distribution at a finer spatial resolution than the LSOA level choropleth, capturing score nuances while providing an overall result understanding. The glyphs, with textured bars and pies for areas with higher barrier scores, illustrate parameter interplay and offer a quick score distribution overview in the area. Relative scores enable analysts to compare decarbonisation parameter behaviour across cells, revealing hidden data patterns not visible in the choropleth map. We apply the same process to Scenario II to find areas with higher needs for energy prioritisation, and Scenario III which equates the weights for all parameters.

Figure 2 shows how the glyphs visualise the prioritised area based on the MCDA calculation. Analysts can capture score nuances, such as avoiding areas with higher socio-demographic parameters visible in the same area with higher final scores. With the gridded-glyphmaps, more details such as proportion of low-cost technology and socio-demographic parameters is apparent. Both top-left area and lower-right area of Cambridge is shown to have around the same overall score in the choropleth map, but with different prevalence of low-cost technology and socio-demographic scores. This allows the analysts to suit their preferences on which area to prioritise, and to further adjust the model. The line chart glyph allows analysts to see which parameters is highly influential to the final score, potentially modifying the weights to emphasise heat pump potential, building insulation, and energy demand, while downplaying socio-demographic weights.

We received positive feedback from AITL on the platform, citing that the highly interactive dashboard is useful to understand spatial distribution of parameters simultaneously. The gridded-glyphmaps also allows for visualising parameters with different level of granularity, which is an important feature currently missing in the LAEP+ platform. We also received feedback from AITL's clients on the need for a collaborative feature, facilitated by the historical line chart glyphs.

Limitations: Discretised geographic data are known to suffer from Modifiable Areal Unit Problem (MAUP), where certain data points might simultaneously fall into different cells [SRH23]. We mitigate this by interactively faciliting different discretisations (through grid offsetting and sizes). Compared to the choropleth maps, using gridded-glyphmap with larger grid sizes also reduce spatial precision where administrative units are smaller. Also, although we can display multivariate data, this approach is not scalable to many

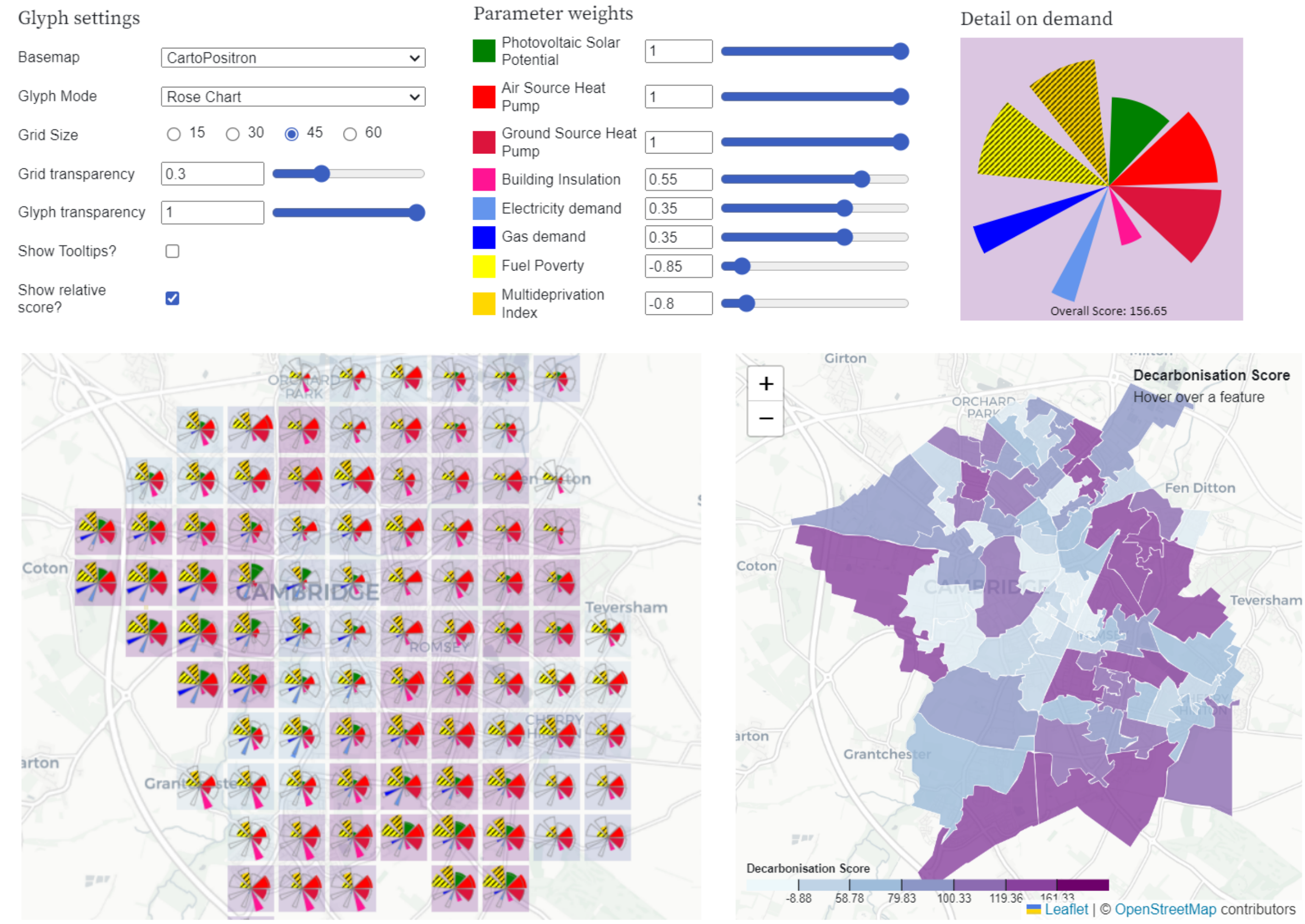


Figure 2: *Interactive interface to facilitate exploration of the MCDA model. Rose Chart glyphs showing gridded parameters, with weights that correspond to a decarbonisation scenario, emphasises the deployment of low-carbon technology equitable to socio-demographic aspects of population. Relative scores indicates that areas with higher overall score might not always represent the optimal alternatives shown in the choropleth map. The glyphs enable insights into the MCDA model, showing areas more suitable to be prioritised based on the parameters' contribution and barriers. The platform is available at* `https://observablehq.com/@danylaksono/multivariate-mcda`.

more variables. The bar chart glyph shows how a large number of variables can overload the cells, compromising their clarity and readability due to the number of bars competing for space. Such multivariate visual complexity is also problematic for users unfamiliar with interpreting such intricate data representations such as higher-level decision makers. We use linear weighting where scores from each parameter are standardised to the same scale without factoring the unit, which is known to affects how the final score is computed [SCCW09]. We also use Simple Additive Weighting (SAW), which in this case facilitates simple decision making scenario. More complex model such as AHP and TOPSIS are more suited for different, more complex scenarios [KSS*17].

6. Conclusions

We demonstrate benefits to integrating geovisualisation with a MCDA framework for multi-criteria decision-making. We introduced the use of a gridded-glyphmap to represent decision-making scenarios in finding suitable location for decarbonisation planning in Cambridge, UK. Utilising the Simple Additive Weighting (SAW) MCDA model on LSOA level geographic data, we demonstrated how this approach allows for a more nuanced visualisation of multivariate parameters. This method not only reveals patterns obscured by traditional MCDA computations but also enables decision-makers to understand how each parameter contributes to the final score. We also show how decision-makers can adjust models based on their preferences, providing a dynamic tool for decision-making in decarbonisation planning.

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