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A methodological approach for enhancing visualization of country data representation in the presence of significant spatial disparity ☆

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ABSTRACT

In this article, we present a methodological approach to address spatial disparity in global data representation, introducing an algorithm called Flexible Mapping to Understand Spatial Analysis (FLEMUSA). We utilize world maps to depict various data points across countries, revealing substantial variation among them. However, conventional choropleth maps often fail to effectively represent regions with sparse data, obscuring valuable insights. To mitigate this issue, we propose interactive graphical methods in both two and three dimensions, implemented through open-source Python code accessible via Google Colab. Our approach includes several contributions such as excluding countries without data from the representation, scaling magnitudes within country borders, focusing on regional analysis, and using logarithmic scales for bubble maps proportional to country sizes. Additionally, we offer interactive 2D and 3D representations, rotatable 3D representations, and zoomable options, facilitating enhanced visualization of regional similarities amidst data heterogeneity. Through this algorithm, we aim to improve the clarity and interpretability of spatial data analysis, integrating solutions for extreme data overdispersion, all programmed with open-source code.

- Utilization of world maps for visual representation of data across countries mitigating the overdispersion step by step.
- Implementation of graphical methods, including interactive 2D and 3D maps, to address spatial disparity.
- Provision of open-source code for customizable graphical representations, facilitating implementation in online journals as interactive code snippets.

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Name and reference of original method:	[1] Brewer, C. A. (1994). Color use guidelines for mapping. Visualization in modern cartography, 1994(123–148), 7. [2] Harrower, M., & Brewer, C. A. (2003). ColorBrewer. org: an online tool for selecting color schemes for maps. The Cartographic Journal, 40(1), 27–37.
Resource availability:	Phyton code is available in: https://colab.research.google.com/drive/10Jw-pyWJO-UmhHH7ovjA0OZmD4FVhl3L?usp=sharing

Background

Throughout history, cartographers have developed different methods to represent geographical data, each with its own strengths and limitations. Ptolemy, a Greek geographer from the 2nd century, is often credited with pioneering the use of coordinate systems and projections to accurately depict the Earth's surface [3]. His work laid the foundation for modern cartography, emphasizing the importance of preserving the geographic integrity of locations through longitude and latitude coordinates. After him, maps have long been recognized as powerful tools for visualizing spatial patterns and understanding geographical phenomena. From the earliest cartographers like Ptolemy to modern Geographic Information Systems (GIS), maps have played a crucial role in representing the world around us [4].

One of the key advantages of maps over other forms of data visualization is their ability to convey complex spatial information in a visually intuitive manner [5]. Unlike tables or graphs, which may require extensive interpretation, maps provide a direct representation of spatial relationships and distributions. This makes them particularly valuable for identifying regional patterns, detecting spatial trends, and communicating geographic insights effectively. Moreover, maps play a crucial role in representing macro-scale phenomena derived from global databases, such as those provided by the World Bank or the International Monetary Fund. These databases offer extensive datasets covering a wide range of indicators, from economic and social to environmental variables. While these data can be expressed per capita or in percentage terms, such representations may still obscure the magnitude of the underlying data [6].

In addition, despite their utility, traditional mapping techniques like choropleth maps have limitations, especially when dealing with datasets exhibiting significant spatial disparity. Uneven distribution of data across geographic regions can lead to misleading visualizations, obscuring important patterns. Sparse observations in some areas may result in exaggerated or misleading representations, undermining the accuracy and interpretability of the map. Furthermore, choropleth maps pose challenges in distinguishing magnitudes of over dispersed data due to imperceptible color scales, which can exacerbate cognitive difficulties in interpreting map patterns [1,2], as we can see in some articles [7–9].

Thus, our motivation is to create an algorithm specifically designed to overcome the limitations of traditional mapping techniques and enhance the visualization of spatial data representation. We recognize the importance of preserving the geographic integrity of locations, as emphasized by pioneers like Ptolemy, while also addressing the challenges posed by spatial disparity in data.

Furthermore, our methodology is designed to be accessible and customizable, leveraging open-source Python code and interactive platforms like Google Colab [10]. This accessibility empowers users to tailor visual representations to their specific research needs, facilitating deeper insights into spatial patterns and phenomena.

In summary, our methodology builds upon the rich tradition of cartography while embracing modern computational tools to offer a robust solution for visualizing global data representation. By providing researchers with the means to create accurate, informative, and visually compelling maps, we aim to advance the field of spatial analysis and contribute to a deeper understanding of our world.

Method details

This method utilizes freely available data on observations per country as an example, specifically public-private partnership (PPP) projects registered by the World Bank (https://ppi.worldbank.org/en/ppidata). Many authors investigate projects from this database [11–14]. The Information is available for a total of 195 countries, each with a variable number of projects. We can analyze the overdispersion data, in Table 1, with descriptive statistics such as mean, median, variance, minimum, and maximum of the number of projects per country:

Table 1
Descriptive statistics of the World Bank Database of Infrastructure Projects.

Mean	104.7
Median	10
Variance	72,038.56
Minimum	0
Maximum	2127

Descriptive statistics in Table 1 point out the existence of overdispersion in the count data of projects per country. Overdispersion refers to a situation where the observed variation in the data is greater than what would be expected from a theoretical model, such as a Poisson or normal distribution. Thus, these data are considered over dispersed because of the following reasons.

The mean project count per country (104.7) is substantially higher than the median (10), indicating that some countries have significantly more projects than others. This discrepancy suggests that there are outliers or extreme values in the data that are pulling the mean upward.

The median project (10) count is much lower than the mean (104.7), indicating that the distribution is skewed to the right. This skewness implies that there are a few countries with very high project counts, which is further evidence of overdispersion.

The variance (72,038.56), which measures the dispersion of data points around the mean (104.7), is considerably larger than the mean itself. This indicates that the data points are spread out widely from the mean, reinforcing the notion of overdispersion.

The minimum project count is 0, indicating that there are countries with no projects at all. On the other hand, the maximum count is 2127 (Brazil), signifying a wide range of project counts across countries. This broad range between the minimum and maximum values contributes to the overdispersion observed in the data.

Overall, the combination of a high mean relative to the median, a large variance, and a wide range between the minimum and maximum values suggests that these project count data are over dispersed, meaning they exhibit more variability than would be expected under a theoretical distribution and showing difficulties to represent the projects per country with a color scale because of visual cognitive limitations.

Thus, the process to visualize the problem in a map is carried out step by step as follows with Python code:

(1) The data on countries and the corresponding number of projects are loaded.
(2) The world map file is loaded.
(3) The project information is combined with the world map, assigning the number of projects to each country.
(4) The poles are removed from the map for clearer visualization and because there are no projects in those locations.
(5) The world map is configured and drawn with color intensities based on the number of projects.
(6) A color bar indicating the number of projects per country is created.

Utilizing open-source code provides a flexible and customizable way to tailor maps according to specific requirements. By leveraging open-source Python libraries like geopandas and matplotlib, users can easily modify map parameters, such as ISO (International Organization for Standardization) country codes and project values, to create personalized visualizations. This adaptability allows researchers and practitioners to adjust the visualization to suit their unique datasets and research objectives.

Users can simply update the ISO_codes list with the desired ISO country codes and the counts list with corresponding project values. This enables the creation of custom maps tailored to specific datasets or research questions. Additionally, parameters such as color schemes, map projections, and legend formating can be easily adjusted within the code to further customize the visualization.

Thus, we can see the number of projects represented in Fig. 1. However, an important limitation is that projects with few or no registered projects in a country may not be distinguishable on the map. This can lead to an underrepresentation of certain countries in the visualization as can also be seen in research articles [15–19].

One solution to this problem is to introduce an additional functionality to handle countries with no observations. Specifically, to filter out countries with zero projects, ensuring that only countries with recorded data are visualized on the map. This refinement enhances the clarity of the visualization by removing unnecessary clutter and focusing solely on relevant data points.

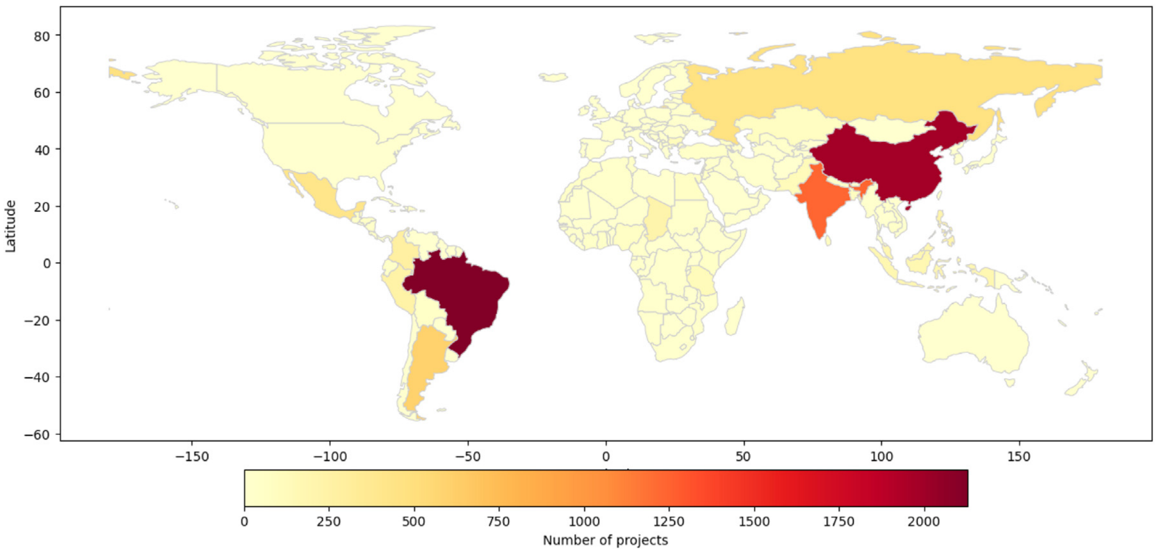


Fig. 1. Choropleth map of project counts by country.

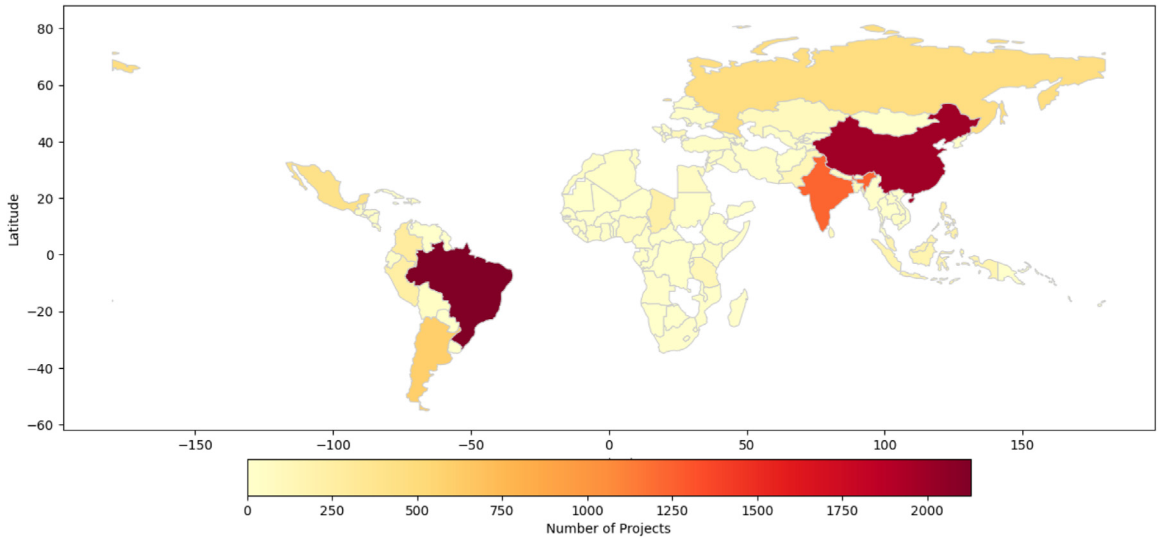


Fig. 2. Choropleth map of project counts by country, excluding zero values.

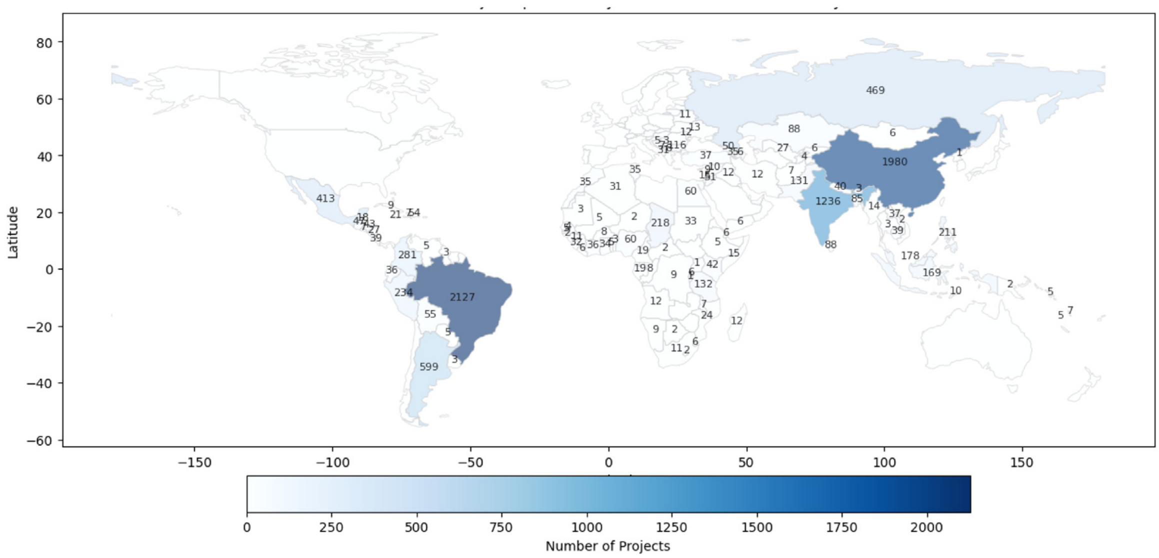


Fig. 3. Choropleth map of project counts by country, showing the number of projects within each country.

By applying a filter, the code ensures that only countries with at least one PPP project are retained in the world data frame (see Fig. 2). Consequently, the subsequent plotting commands will only visualize countries with recorded projects, effectively addressing the issue of visualizing countries without observations.

Even when excluding the empty values, the few observations are not well visualized. As we can see in Fig. 3, although this can be addressed by setting the value to a number, countries with small surface overlap, and do not display clearly.

In these cases, one option is to focus the analysis on regions to reduce the dispersion within each one, allowing for shorter scales, better color discrimination, and clearer visibility of magnitudes within each country without overlap and marked with red color, as can be seen in Fig. 4 with the African continent.

Alternatively, we propose code for a complementary visualization approach using bubble maps (Fig. 5), which can be useful in some cases. This code visualizes the number of projects per country using bubble sizes proportional to project counts. Despite its virtues, due to the variable sizes of the bubbles, accurately identifying the origin of each bubble remains challenging.

Thus, since this method may not provide a clear representation of spatial patterns and could potentially obscure smaller countries or regions with fewer projects, we propose code for another two methods: one calculates the size of each bubble in logarithmic scale, and another scales the bubbles proportionally to the area of the country to prevent them from exceeding their boundaries.

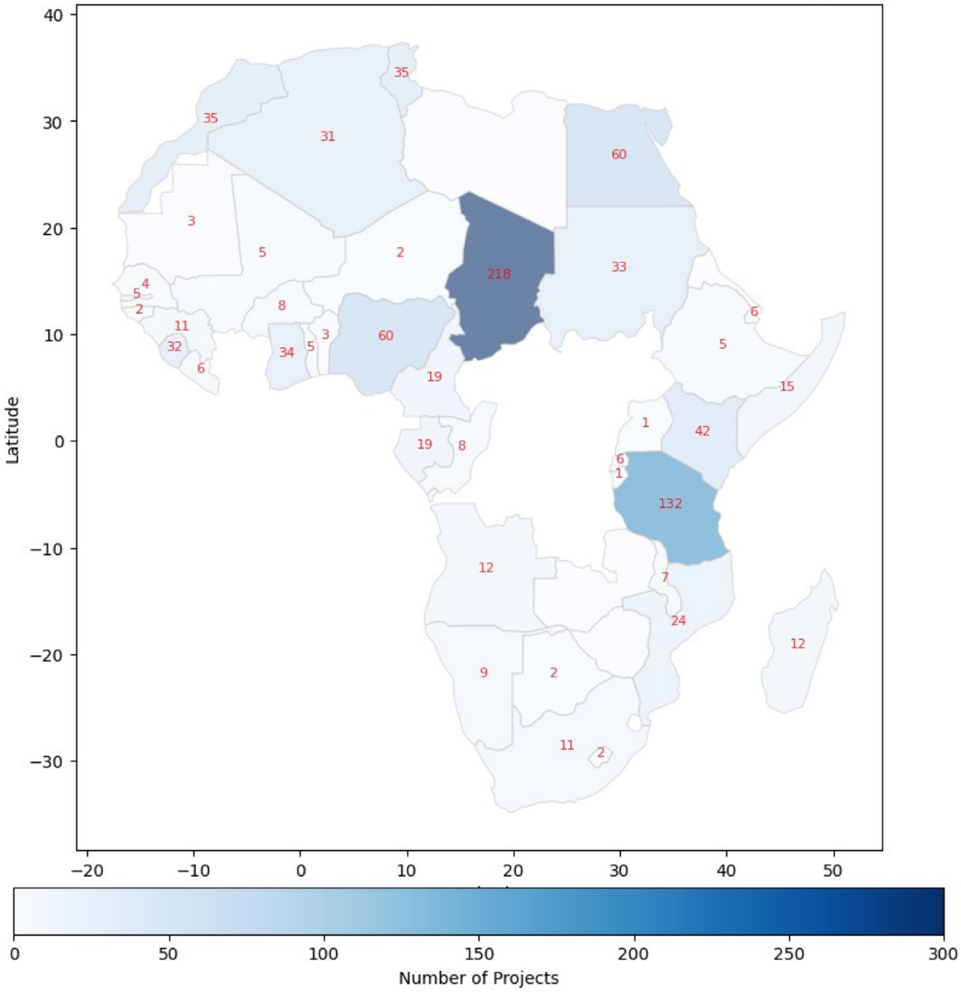


Fig. 4. Choropleth map of project counts by country in Africa, showing the number of projects within each country.

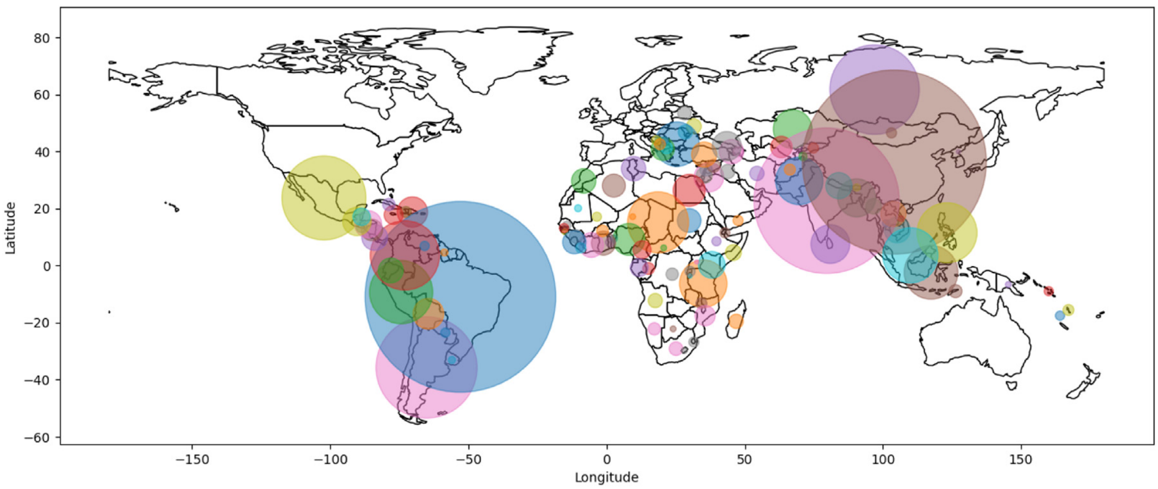


Fig. 5. Bubble map of project counts by country.

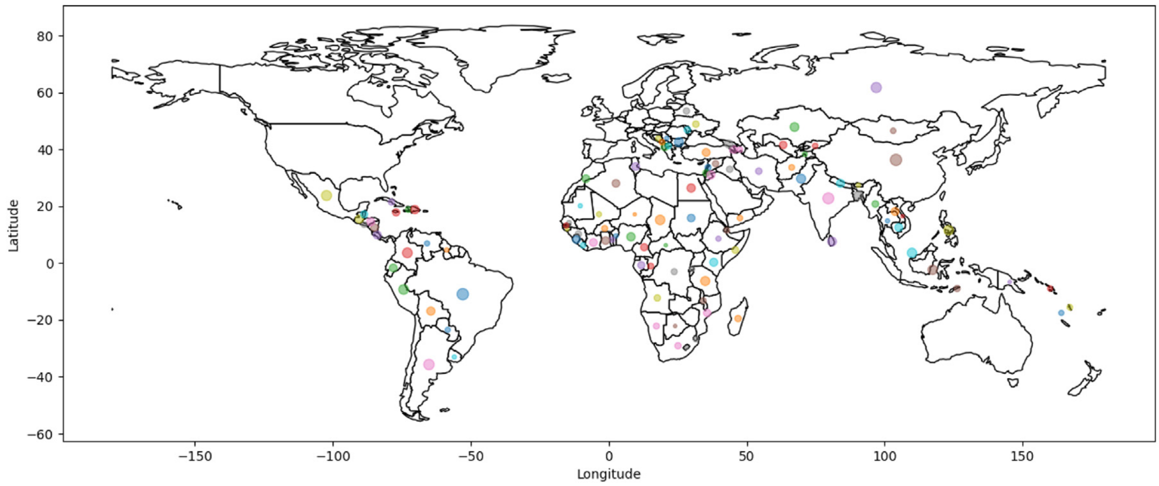


Fig. 6. Bubble map of project counts by country in a logarithmic scale.

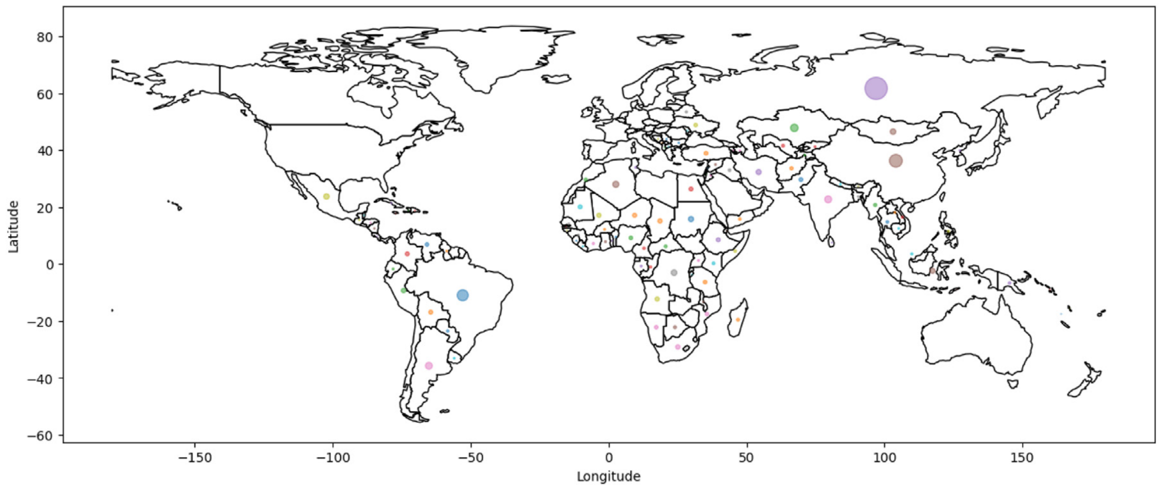


Fig. 7. Bubble map of project counts adjusted by country surface.

In the logarithmic scale code, we adjust the size of each bubble using a logarithmic scale (see Fig. 6). This adjustment is made by applying the natural logarithm function (np.log()) to the project count (count) before multiplying it by a scaling factor, as it can be consulted in the Google Colab.

In the second case, we can program that the number of projects does not exceed the area of each region as follows (Fig. 7).

In addition to these visualization methods, there are other effective ways to represent data. Another alternative is to use interactive maps (see Fig. 8). The advantages of this representation over choropleth maps are three. The first one is the direct interpretation since the scatter plots provide a direct visualization of project counts for each country without the need for color interpretation. The second one is the avoidance of size distortion since choropleth maps may distort the size of countries based on their geographic area, potentially misleading viewers. Scatter plots avoid this by using marker size to represent data values. The third one is interactivity: The Plotly Express plot is interactive, allowing users to hover over markers to explore specific data values and country names (see Video 1 with code available in Google Colab to rotate freely).

In summary, this approach offers a straightforward and intuitive way to visualize spatial data, providing an alternative to choropleth maps that can be particularly useful for exploring and understanding project distribution across countries.

We also propose code to leverage the benefits of maintaining representation by longitude and latitude while visualizing data by position. By implementing this code, we can effectively map the distribution of projects across countries.

The code utilizes geospatial data to plot project counts per country on a map, utilizing longitude and latitude coordinates (see Fig. 9). This approach preserves the accurate geographic context, facilitating the identification of spatial disparities in project distribution. Additionally, by representing data in a three-dimensional space, the code enhances the visualization of project counts (axis Z), making it easier to identify countries with varying levels of project activity.

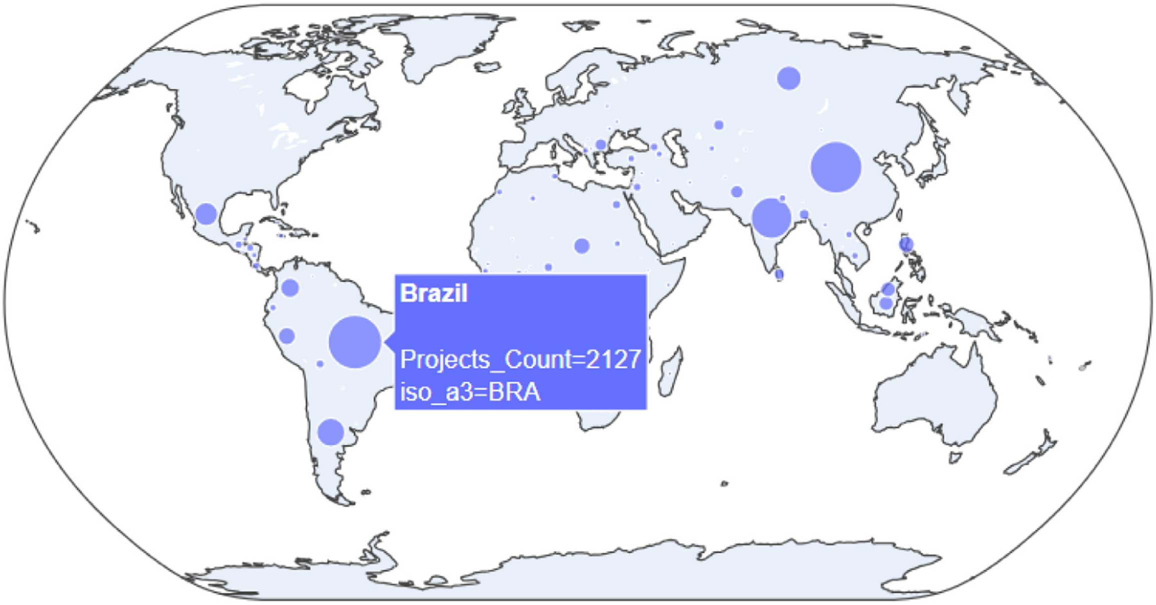


Fig. 8. Two-dimensional interactive and zoomable map of project counts by country, featuring Brazil (BRA with 2127 projects).

Video. 1. Interactive 2D map showing the number of projects per country with open-source code. Source: Own elaboration from https://youtu.be/sObSjVOigBg.

The code includes functionality to distinguish the top-performing countries with the most projects from the rest. Thus, in Fig. 9, we highlight Brazil (BRA), China (CHN), India (IND), Russia (RUS), and Argentina (ARG) as examples showing their ISO code, and the rest of the observations with fewer counts without showing their ISO codes.

The advantages of this proposal are the following:

1- Respect the spatial location of the data (X and Y axes).
2- Accounting for the number of projects (Z axis).

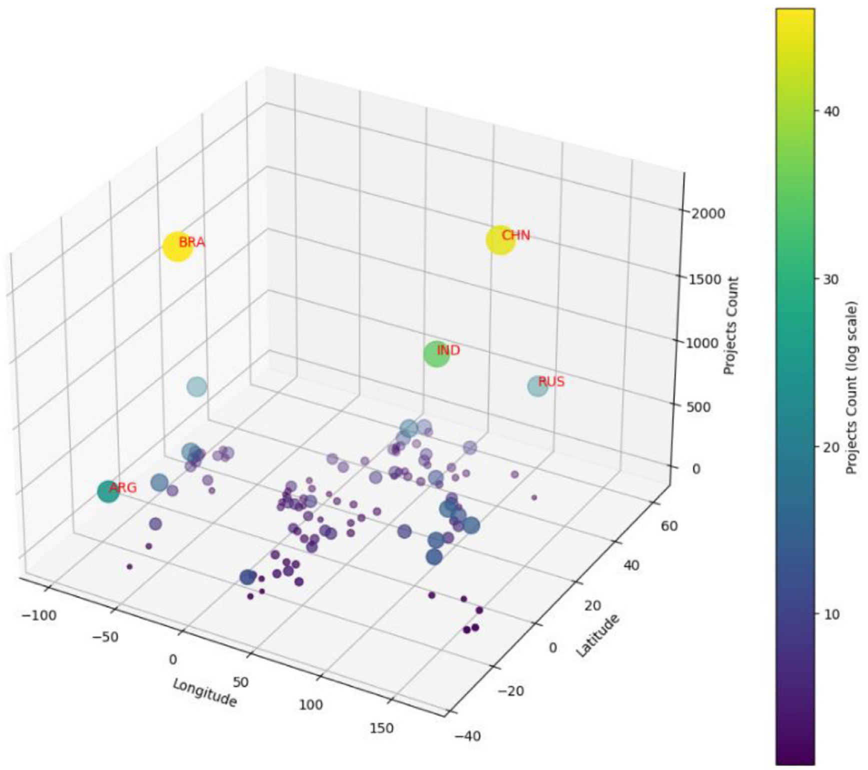


Fig. 9. Number of projects per country, highlighting the top 5 (Brazil, BRA; India, IND; Russia, RUS; Argentina, ARG) according to longitude and latitude.

3- Allows you to choose the "n" locations of interest to show their ISO code.
4- Corrects possible perspective biases by incorporating a scale of both, color and bubble size, in logarithmic proportion.

Despite the benefits of this way of representing, we have to be careful because the devil is in the details. The data for some countries may appear to not match the graph due to the perspective used. This can happen because the 3D scatter plot distorts the perception of the data, especially when viewing it from an angle. In this code, we are plotting countries on a 3D scatter plot using their centroids' coordinates as the X and Y positions, and the number of projects as the Z position. However, because the plot is in 3D and we are viewing it from a specific angle, the size and position of the bubbles may not accurately represent the actual level and distribution of the projects. For example, if a country has a cluster of projects in one region but the centroid is in another, the bubble representing that country may appear in an unexpected location on the plot, leading to a discrepancy between the data and the visualization.

To mitigate this inconvenient, and as we did with the 2D Maps, one approach is to use alternative visualization techniques that provide a clearer representation of the data, such as providing interactive controls for users to adjust the perspective can also help improve the interpretability of the 3D scatter plot (see Fig. 10 and Video 2). In the Colab, we provided code to make the representation interactive and also to directly display the magnitude and ISO code of the country. We include a screenshot of its application in Europe because, for visualization in a written article, there is less overlap among countries (see Fig. 11).

The utilization of a three-dimensional (3D) scatter plot to visualize project data represents a significant advancement in data visualization techniques. Traditionally, geographical data has been represented on two-dimensional (2D) maps, which inherently restrict the depth of analysis due to the absence of a third dimension. However, by leveraging 3D visualization tools such as Plotly, researchers and analysts can now explore spatial data with enhanced depth and interactivity.

Consider the dataset provided in the code, which includes the number of projects per country. By plotting this data on a 3D scatter plot, each country's position is determined by its latitude and longitude coordinates, while the height of the data point (or "bubble") represents the number of projects hosted by that country. For instance, Afghanistan, with 7 projects, would be represented by a bubble positioned according to its geographical coordinates, with a height corresponding to the project count.

This representation offers several academic advantages. Firstly, it allows for enhanced spatial understanding, enabling researchers to visually perceive the spatial distribution of projects while simultaneously understanding the variations in project count across different regions. For example, Brazil's significantly higher number of projects (2127) would be represented by a taller bubble compared to neighboring countries with fewer projects.

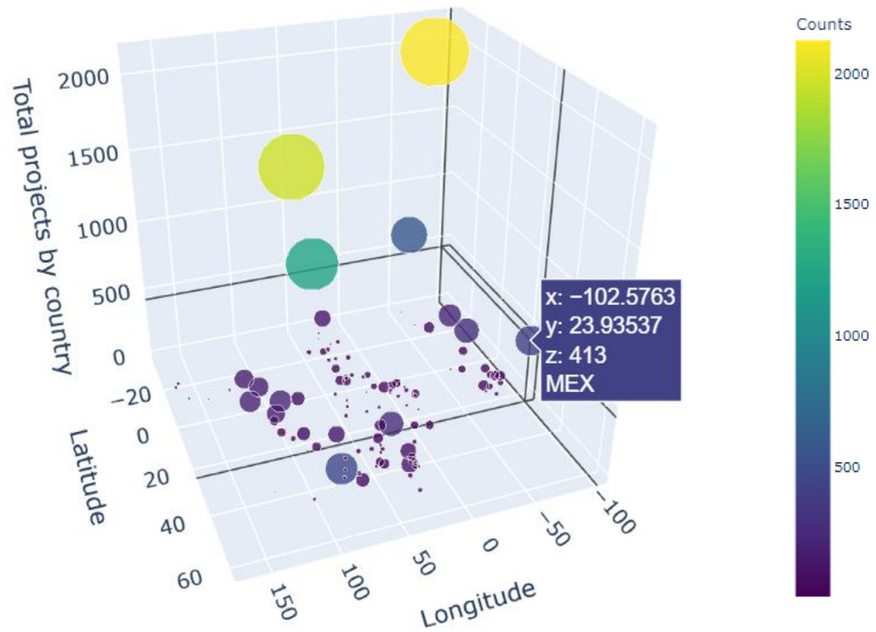


Fig. 10. Three-dimensional Interactive, rotatable, and zoomable map displaying the number of projects per country, featuring Mexico (MEX) with 413 projects.

Moreover, the interactive nature of 3D scatter plots facilitates improved data exploration. Researchers can interactively rotate the plot, zoom in on specific regions, and hover over data points to reveal detailed information. This level of exploration fosters a deeper understanding of spatial patterns and facilitates hypothesis generation for further analysis.

Additionally, 3D scatter plots enable the representation of multidimensional data. Beyond geographical coordinates, additional dimensions such as project volume investment, duration, or delays can be represented through bubble size or color. For instance, countries with higher project volume investment could be depicted with larger bubbles, while color gradients could signify variations in project duration or type of partnership.

Finally, these visualizations serve as effective communication tools for conveying research findings to diverse audiences. Whether included in academic papers, presentations, or online articles, visually engaging 3D scatter plots enhance the clarity and impact of the research findings. They allow researchers to communicate complex spatial relationships and trends in a compelling and accessible manner, thus facilitating knowledge dissemination and collaboration within the academic community.

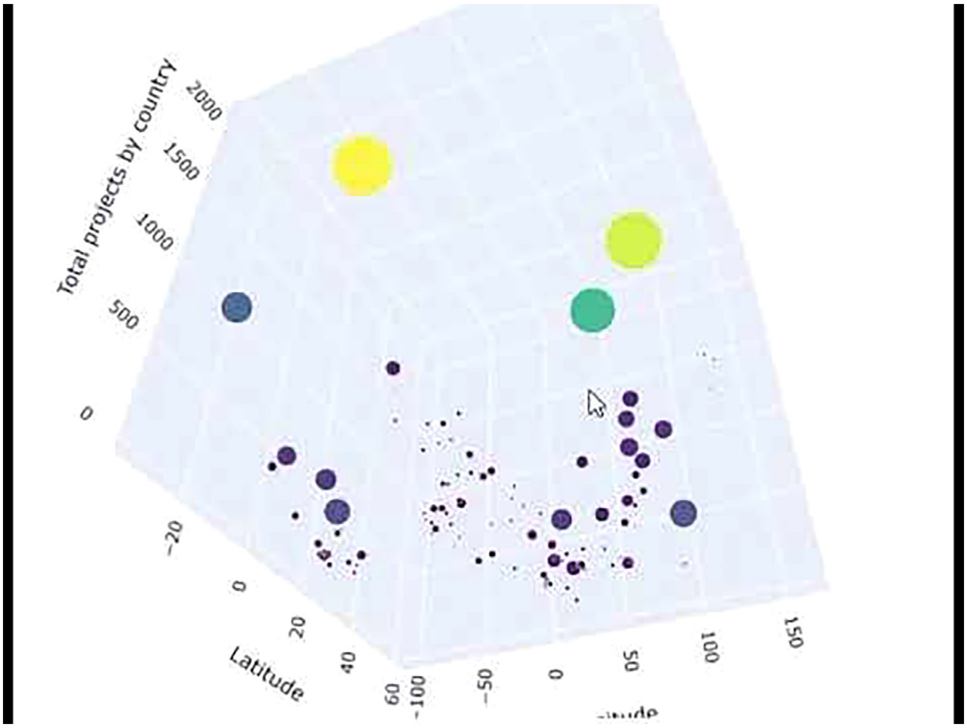
Based on the previous steps, we propose a decision algorithm called the FLEMUSA method (FLExible Mapping to Understand Spatial Analysis). It is in Fig. 12 where we outline this step-by-step process with various alternatives, including our contributions of original solutions such as:

- Removing countries without data from the representation,
- Placing magnitudes within country borders,
- Focusing analysis on regions,
- Rescaling bubble maps on logarithmic scales,
- Proportionally restricting them to country surfaces,
- Interactive 2D and 3D representations,
- Rotatable 3D representations, and zoomable options.
- In the case of static 3D maps, enriching the cognitive process by displaying the absolute number of projects on the Z-axis, while the magnitude size represented, the bubble, is on a logarithmic scale and in accordance with a different color scale.

Thus, innovation can be seen in an integrated process, with proposals and solutions for extreme overdispersion (in different degrees), as well as original suggestions, all programmed together with open code.

Method validation

The method of creating maps using open-source Python and Google Colab allows for standardized and free validation from anywhere in the world, with the advantage of being non-proprietary software. This approach leverages the power of open-source tools and cloud computing to democratize access to geographic data analysis and visualization. By utilizing Python libraries like GeoPandas and Plotly, combined with the accessibility of Google Colab for collaborative and remote work, individuals and organizations can



Video 2. Three-dimensional map of project counts by country, demonstrating rotation, zoom, and interactivity. Source: Own elaboration from https://youtu.be/8FX3vek_E0k.

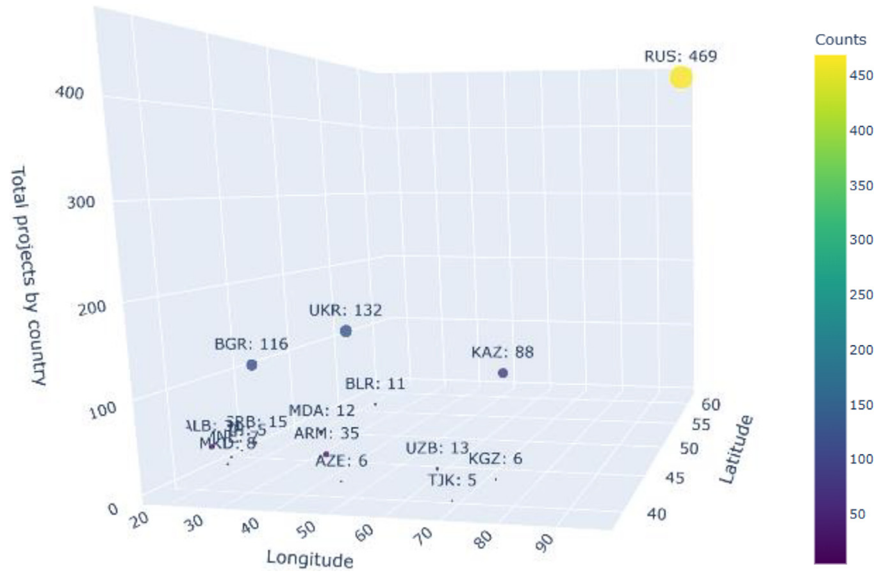


Fig. 11. Zoomable, three-dimensional rotating interactive map illustrating project distribution across Europe, showing ISO codes and magnitudes.

conduct geospatial analysis, create interactive maps, and share insights without being restricted by proprietary software or expensive licensing fees. This democratization of mapping technology fosters innovation, collaboration, and transparency in spatial data analysis.

For instance, our methodologies can be applied to visualize inequality indices such as Gini coefficients, poverty rates, or access to basic services across countries or regions. For example, using data from the World Bank's World Development Indicators, researchers can create interactive maps showing income inequality across different regions, facilitating targeted policy interventions.

Another application lies in analyzing violence and crime rates. Researchers can use our methods to map homicide rates, crime hotspots, or rates of domestic violence by geographic location. By integrating data from sources like the United Nations Office on

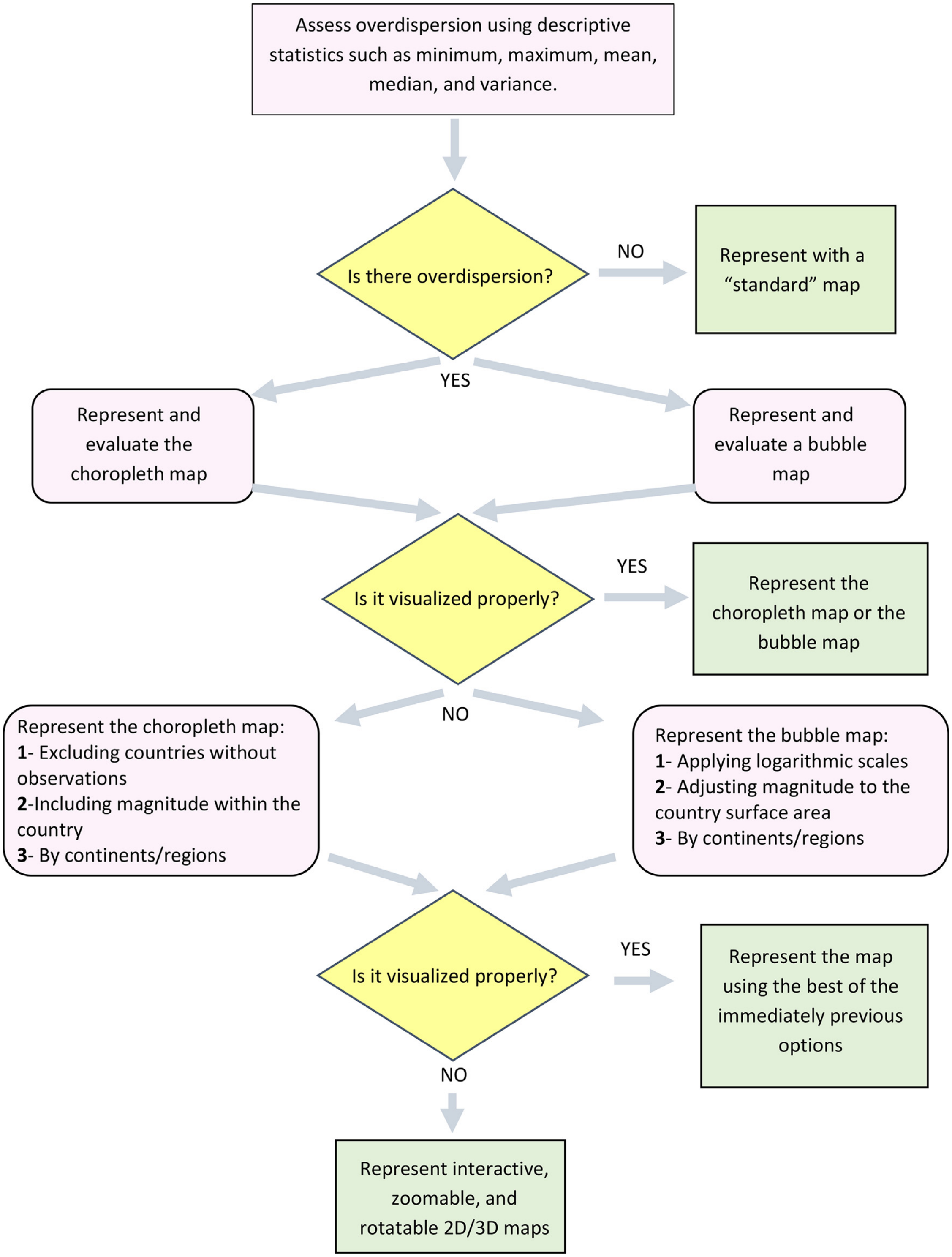


Fig. 12. Decision algorithm for representing overdispersed magnitudes while respecting their spatial location.

Drugs and Crime or national police statistics, interactive maps can illustrate spatial patterns of violence, aiding in crime prevention strategies.

Our methodologies can also contribute to the analysis of terrorism incidents and their spatial distribution. Researchers can map terrorist attacks, casualties, or extremist group activities across regions using data from the Global Terrorism Database. Interactive visualizations can provide insights into geographic patterns of terrorism, supporting efforts in counterterrorism and conflict resolution.

Additionally, the code can be embedded in documents and research articles as an executable, allowing for seamless integration of interactive maps and data visualizations into scholarly publications. This capability reinforces the reproducibility and transparency of research findings, enabling readers to interact with the underlying data and methodology directly within the document. By incorporating executable code alongside descriptive text and visualizations, researchers can effectively communicate their methods, results, and insights while fostering greater engagement and understanding among readers.

Limitations

Not applicable.

Ethics statements

Not applicable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Jorge Fleta-Asín: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Fernando Muñoz:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Carlos Sáenz-Royo:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Data availability

The data are public and available

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References

[1] C.A. Brewer, Color use guidelines for mapping, Visual. Mod Cartogr. 1994 (123–148) (1994) 7.
[2] M. Harrower, C.A. Brewer, ColorBrewer. org: an online tool for selecting colour schemes for maps, Cartogr. J. 40 (1) (2003) 27–37.
[3] N.J. Thrower, Maps and civilization: Cartography in Culture and Society, University of Chicago Press, 2008.
[4] J.B. Harley, The New Nature of maps: Essays in the History of Cartography (No. 2002), JHU Press, 2002.
[5] M. Monmonier, How to Lie With Maps, University of Chicago Press, 2018.
[6] A.M. MacEachren, D. DiBiase, Animated maps of aggregate data: conceptual and practical problems, Cartogr. Geograph. Inform. Syst. 18 (4) (1991) 221–229.
[7] J. Fleta-Asín, F. Muñoz, Risk allocation schemes between public and private sectors in green energy projects, J. Environ. Manage. 357 (2024) 120650.
[8] J. Fleta-Asín, F. Muñoz, Institutional distance and US-based international mutual funds' financial performance, Finance Res. Lett. 51 (2023) 103412.

[9] J. Fleta-Asín, F. Muñoz-Sánchez, J.M. Gimeno-Feliú, Does the past matter? Unravelling the temporal interdependencies of institutions in the success of public–private partnerships, Public Manag. Rev. (2022) 1–27.
[10] T. Kluyver, B. Ragan-Kelley, F. Pérez, B.E. Granger, M. Bussonnier, J. Frederic, … C. Willing, Jupyter Notebooks-a publishing format for reproducible computational workflows, Elpub 2016 (2016) 87–90.
[11] M.S. Basílio, The determinants of multilateral development banks' participation in infrastructure projects, J. Infrastruct. Develop. 6 (2) (2014) 83–110.
[12] A. Jiménez, M. Russo, J.M. Kraak, G.F. Jiang, Corruption and private participation projects in Central and Eastern Europe, Manag. Int. Rev. 57 (5) (2017) 775–792.
[13] H. Wang, Y. Liu, W. Xiong, J. Song, The moderating role of governance environment on the relationship between risk allocation and private investment in PPP markets: evidence from developing countries, Int. J. Project Manag. 37 (1) (2019) 117–130.
[14] J. Fleta-Asín, F. Muñoz, How does risk transference to private partner impact on public-private partnerships' success? Empirical evidence from developing economies, Socioecon. Plann. Sci. 72 (2020) 100869.
[15] J. Fleta-Asín, F. Muñoz, Renewable energy public–private partnerships in developing countries: determinants of private investment, Sustain. Develop. 29 (4) (2021) 653–670.
[16] J. Fleta-Asín, F. Muñoz, "Sand" or "grease" effect? The impact of corruption on the investment volume of public– private partnerships, Int. J. Emerg. Mark. 18 (5) (2023) 1168–1186.
[17] J. Fleta-Asín, F. Muñoz, When bigger is better: investment volume drivers in infrastructure public-private partnership projects, Socioecon. Plann. Sci. 86 (2023) 101473.
[18] J. Fleta-Asín, F. Muñoz, J Rosell-Martínez, Public-private partnerships: determinants of the type of governance structure, Public Manag. Rev. 22 (10) (2020) 1489–1514.
[19] J. Fleta-Asín, F. Muñoz, C. Sáenz-Royo, Unravelling the influence of formal and informal institutions on the duration of public concessions, Socioecon. Plann. Sci. 101966 (2024).