Redesigning Climate Risk Heatmap for Improved User Experience

Part 1: Theory – Critical Engagement with Visualization Methodologies

The visualization originates from the 2019 Amazon research *Leveraging the Cloud for Rapid Climate Risk Assessments*. It presents heat stress risk scores for a subset of publicly listed companies' corporate facilities, as recorded in the Four Twenty Seven global database. Each facility is represented by a colored dot, with the color corresponding to its level of exposure to extreme heat. The color gradient ranges from green, indicating low heat stress risk, through yellow and orange, to red, which signifies high risk. This map offers a clear visual representation of the geographic variation in climate-related heat exposure across corporate assets globally.

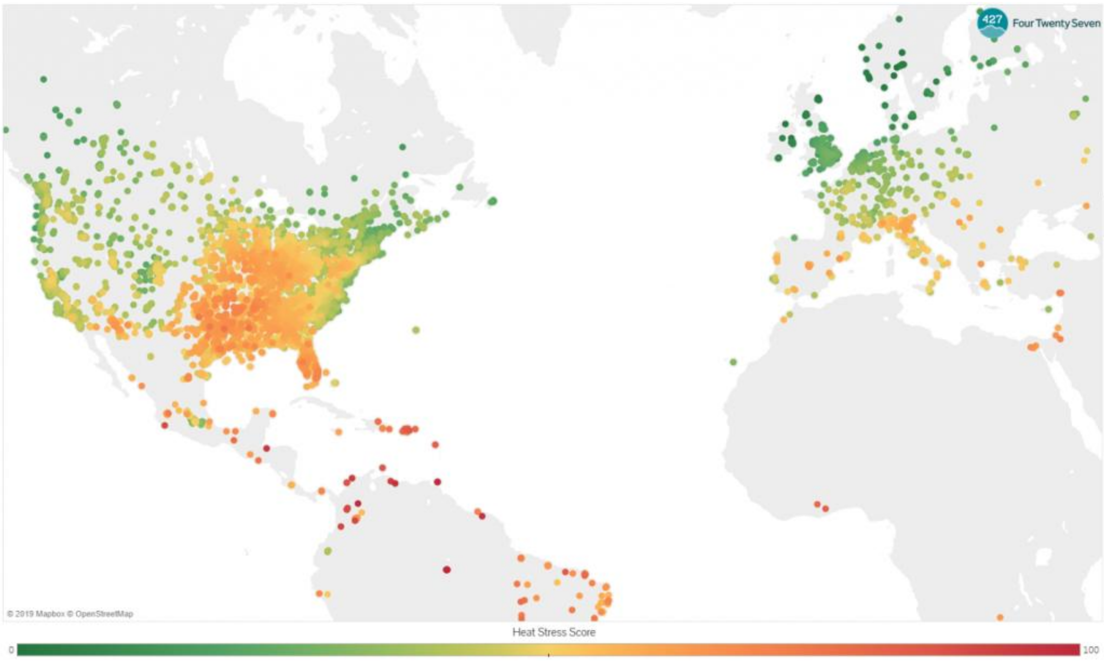

Figure 1. Heat stress exposure for corporate facilities (Gannon 2019).

Admittedly, this visualization is generally effective in showing the geographic location of each facility and its corresponding heat stress risk level. However, it still has some limitations in the application of visualization theory and the clarity of actual presentation. In the following paragraphs, I will evaluate this visualization from both theoretical and practical levels.

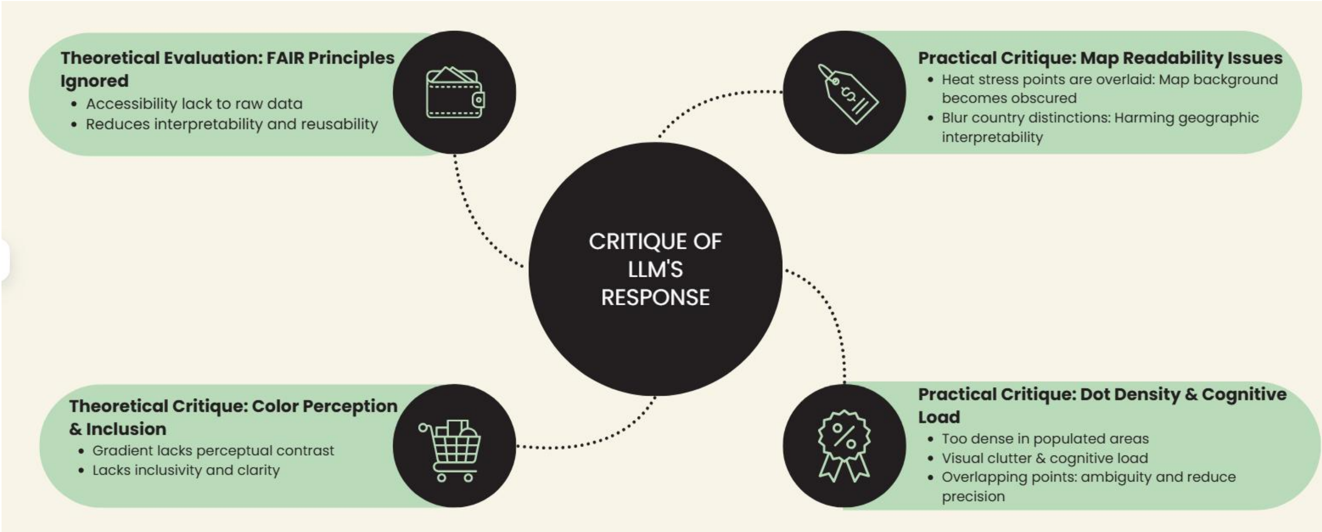

Figure 2. Critique of the Visualization (made by Canva)

Theoretically, the visualization ignores the FAIR data framework. One of its key components - accessibility - emphasizes that once users find data, they must know how to access and use it (GO FAIR, 2019). This includes data availability, clear documentation, and transparent design. Visualization fails in this respect because it does not provide access to the raw data set or explain how heat stress scores are generated or encoded. This lack of transparency undermines the interpretability and reusability of visualizations in academic, institutional, or policy contexts.

Secondly, the color differentiation in this visualization is limited, which can distort users' interpretations. From the perspective of affective design, color choices significantly influence how users perceive and understand information (He et al., 2014). While most users can distinguish between red and green, the gradient between yellow and red lacks sufficient contrast—especially in densely clustered areas—potentially leading to misjudgments. According to the FAIR data principles, a well-designed color scheme should accommodate diverse audiences, including those with color vision deficiencies or those who rely on assistive technologies (Wilkinson et al., 2016). For instance, individuals with severe color vision deficiency may perceive both red and green as shades of brown, making it difficult for them to accurately interpret risk levels based on color cues alone (Shaffer, 2016). Therefore, designers should consider using colorblind-friendly palettes in visualization.

From a practical standpoint, although the visualization appears to have a visually clear map background, it becomes blurred once the heat stress data points are overlaid—particularly in the southeastern United States and certain parts of Europe. As a result, the distinctions between countries or regions become indistinct, which severely limits the geographic interpretability of the map, especially when it is intended to support regional risk assessments.

Furthermore, while the size of individual points seems appropriate, the high density of dots in densely populated areas leads to visual clutter, reducing overall readability and increasing the cognitive load on users. The overlapping colored points introduce ambiguity, making it difficult to interpret the data accurately—particularly in contexts such as facility-level risk assessments, where precision is critical (Wilkinson et al., 2016).

In order to improve the visual design, country and regional labels and more apparent borderlines should be added so that users can identify geographical locations more accurately. Second, scatter maps can replace heat maps or hexagon aggregation maps for overlapping points and mixed colours to reduce visual clutter and provide a clearer picture of regional risk distribution. In terms of color design, it is recommended to use a more differentiated color scheme and use a gradient scale with clear numerical labels (such as 0, 25, 50, 75, 100), such as "0-25 for blue, 25-50 for green, 50-75 for yellow, 75-100 for red" to improve user perception accuracy. In addition, annotations or callouts of high-risk areas can be added to the graph to support risk warnings and enterprise decision-making.

Python or Amazon QuickSight tool can help optimize the original visual design. For instance, it can use context libraries to add base maps (such as grayscale world maps) below the data and enhance country boundaries to help users better locate where the data is located. At the same time, hexbin maps can be introduced to group geographically close data points into the same hexagon and color them according to each hexagon's average thermal stress score. By using a highly differentiated colour scheme, this approach not only effectively reduces the visual confusion caused by point overlap but also more intuitively shows the risk distribution pattern of different regions.

Part 2: Research – Literature-Inspired Analysis

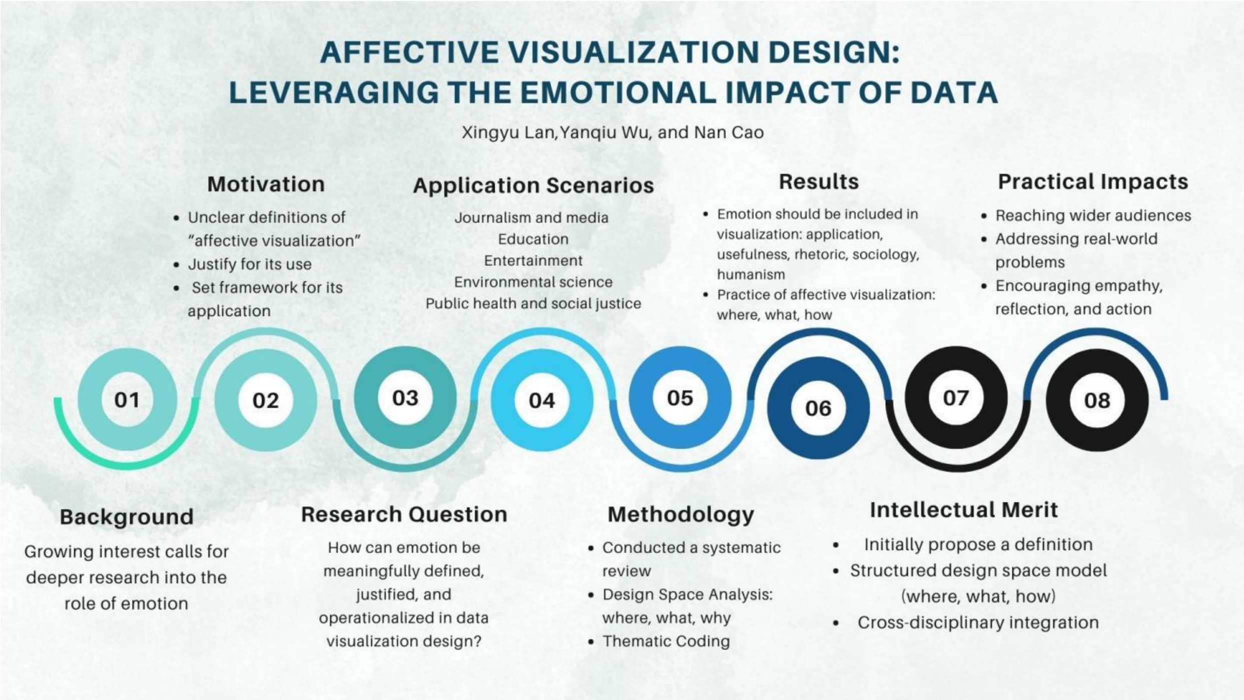

Figure 3. Flowchart for the Affective Visualization Design (made by Canva)

Mainstream chart design has traditionally prioritized objectivity, accuracy, and clarity, often viewing emotional elements as detracting from the rational communication of data (Tufte, 2001). However, a growing body of research challenges this perspective and defends the inclusion of affection in data visualization (Boy et al., 2017). Affective elements can enhance user engagement, memory retention, and comprehension, offering a more layered, human-centred approach to visual communication.

Despite its potential, affective visualization still faces three significant challenges. First, there is a lack of consistency in how the term "affective visualization" is defined. Second, the field lacks systematic justification for why emotion should be integrated into visualization design. Third, no clear framework outlines where affective visualization should be applied, what it should aim to achieve, and how it should be practically implemented (Lan, Wu, and Cao, 2024).

To address these issues, Lan, Wu, and Cao explore how affection visualization can be meaningfully defined, justified, and operationalized (2024). The authors conducted a systematic literature review and thematic coding of 109 academic papers on emotional visualization design. They identified five major argumentative perspectives supporting emotional design: application-based, practical, rhetorical, sociological, and humanistic. Furthermore, they analyzed 61 real-world affective visualization projects, organizing them by design context (where), design goals (what), and design methods (how) (Lan, Wu, and Cao, 2024).

This research makes significant contributions. Theoretically, it offers an unified definition of affective visualization and demonstrates that emotion can enhance data's relevance, communicative power, and resonance. It also provides the first structured framework for understanding and evaluating affective design in data visualization. Practically, it offers guidance for developers, policymakers, and toolmakers to create emotionally resonant visualizations that reach wider audiences, foster empathy, and inspire meaningful action to address real-world social issues (Lan, Wu, and Cao, 2024). The practical applications of affective visualization are evident in domains such as environmental communication, public health, journalism, and social justice, where data is used to inform and provoke empathy and awareness (Lan et al., 2021; Lan et al., 2022). For instance, during the COVID-19 pandemic, many visual narratives were designed to evoke emotional responses—such as shock, fear, or grief—related to the death toll, thereby increasing the impact and urgency of public communication (Bartram, Patra, and Stone, 2017).

Despite these contributions, challenges remain. The limited number of empirical studies cannot fully evaluate the actual effect of emotion visualization technology on decision-making. Furthermore, many technologies and their effectiveness have not been effectively evaluated (Lan, Wu, and Cao, 2024). In the future, more experimental studies of the impact of emotion can be conducted to quantify how emotion affects data interpretation, recall, and behavior. New technologies can also be introduced to study how emerging technologies such as VR/AR, multi-sensory interaction, and 3D printing affect emotional responses. Similarly, researchers also need to continually improve interactive tools that enable non-experts to create emotional visualizations while ensuring usability and accessibility (Lan, Wu, and Cao, 2024).

Part 3: Practice – Tool-Driven Redesign Preparation

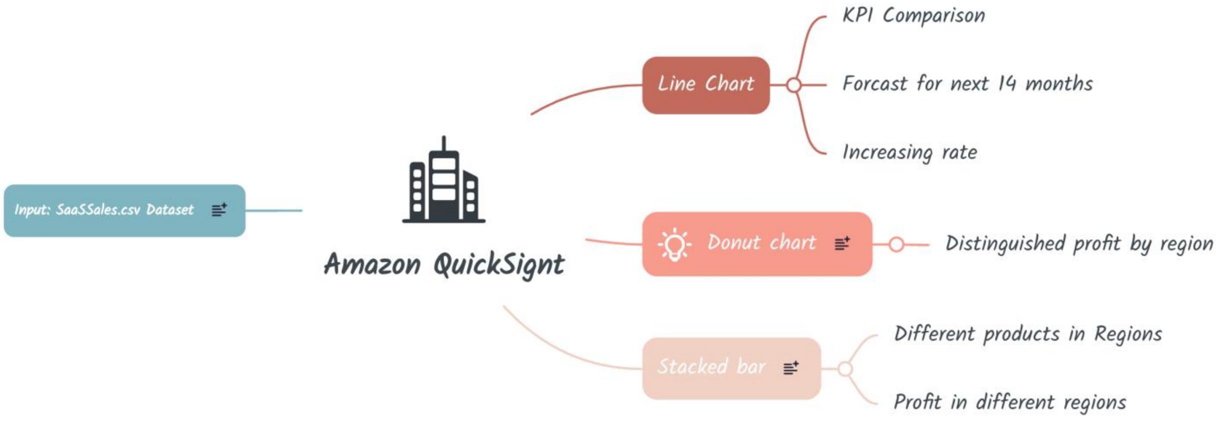

Figure 4. Flowchart by creating Amazon QuickSight (made by Canva)

To explore practical tools that support effective data visualization, I used Amazon QuickSight to work with a SaaS (Software as a Service) dataset consisting of 9,994 records. The dataset contains 9,994 records, covering 2022 to 2025, and contains variables such as Sales, Profit, Discount, Product category, Region, and Subregion. In order to conduct a more targeted data analysis, I focused on four variables: total Profit, Order Date, Subregion and Product for visualization and trend insight.

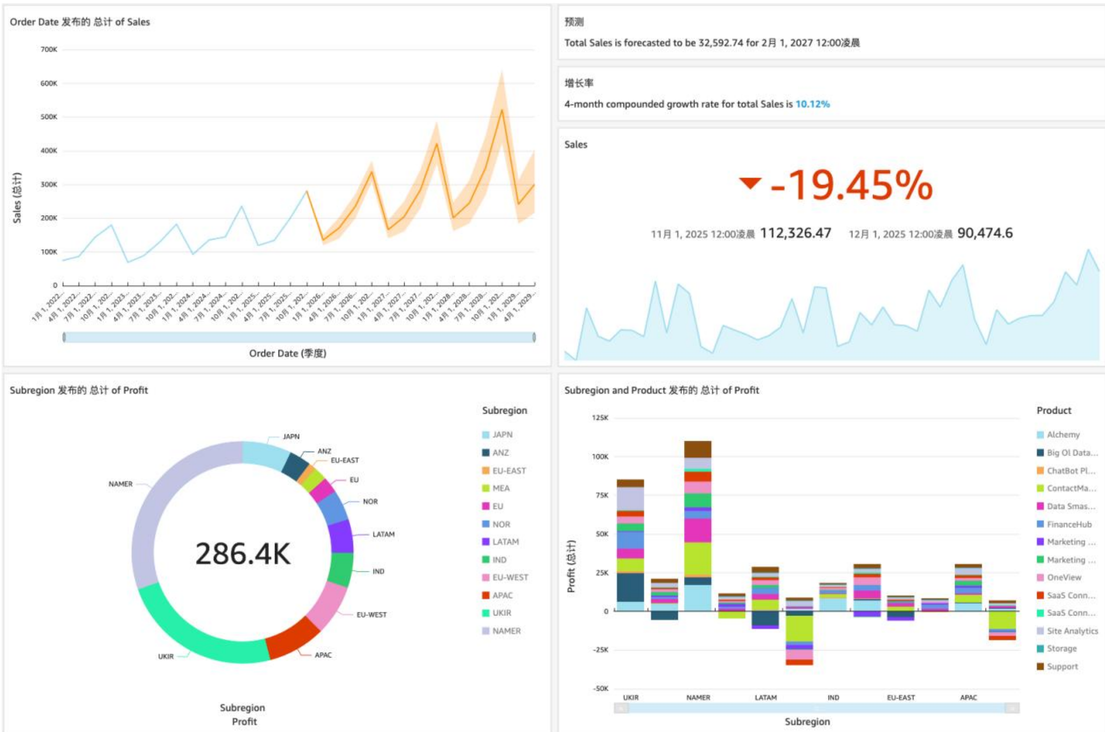

Figure 5. Experiment with Amazon QuickSight

The line chart (top left) illustrates monthly sales trends from 2022 to 2025, showing a steady upward trend in overall sales with clear seasonal spikes, which can be influenced by quarterly cycles. The orange-shaded areas in the chart show projected sales values, which continue the same seasonal fluctuations. The forecast shows that the total sales volume in February 2027 will reach 32,592.74, while the compound growth rate of 10.12% in the last four months highlights the good growth trend of the enterprise in the medium to long term. However, the KPI chart (top right) highlights a 19.45% drop in sales in December 2025 compared to November. This unusual fluctuation could indicate seasonal variations, supply chain disruptions, or market trends that require further investigation.

The donut chart (bottom left) shows the total profit by subregion of 286.4K. NAMER (North America) contributes the most to profits, followed by UKIR (United Kingdom and Ireland) and APAC (Asia-Pacific region). To gain a deeper understanding of each region's profit composition and product performance, the stacked bar (bottom right) provides a detailed visualization of the product profit distribution for each subregion. Notably, there are significant negative profits in regions such as Japan and ANZ (Australia and New Zealand), indicating areas where the company might need to reassess pricing strategies, marketing efforts, or operational costs.

Amazon QuickSight provides a user-friendly data visualization platform. Its application provides a wide range of basic chart types and analysis tools that enable users to generate insights quickly, which is incredibly convenient for individuals with limited experience in data analysis or coding. Moreover, QuickSight can share folders, which enables teams to work together, thus increasing team productivity (Iyer, 2025).

However, it may still not be intuitive enough for first-time users. Key features such as data conversions, calculated fields, and layered filters require multiple clicks or are hidden in menus, making learning more difficult. In my own experiments, it took me some time to figure out how to layer filters across multiple visual components and effectively manage field Wells.

In future improvements, QuickSight may need to simplify the interface by making frequently used features more accessible. For instance, QuickSight should allow users to edit calculated fields directly within the chart view, rather than requiring them to open a separate menu, making adjustments faster and more intuitive.

Part 4: Innovation – Final Redesign and Integration

Since the original data set could not be accessed, I chose the global climate risk index and related economic loss data set from Kaggle. The dataset brings together data from the Germany Watch Climate Risk Index report and other reliable global sources to provide reliable indicators such as the number of climate-related deaths, economic losses and CRI (Climate Risk Index) scores for each country. Its credibility is supported by its transparency, the sources of its peer-reviewed reports, and the wide adoption of academic and policy literature.

Data access link:
https://www.kaggle.com/datasets/thedevastator/global-climate-risk-index-and-related-economic-l

This redesign mainly uses amazon QuickSight. Compared to the original heat stress visualization, my redesign in Figure 6 and 7 provides a broader and deeper perspective on climate vulnerability.

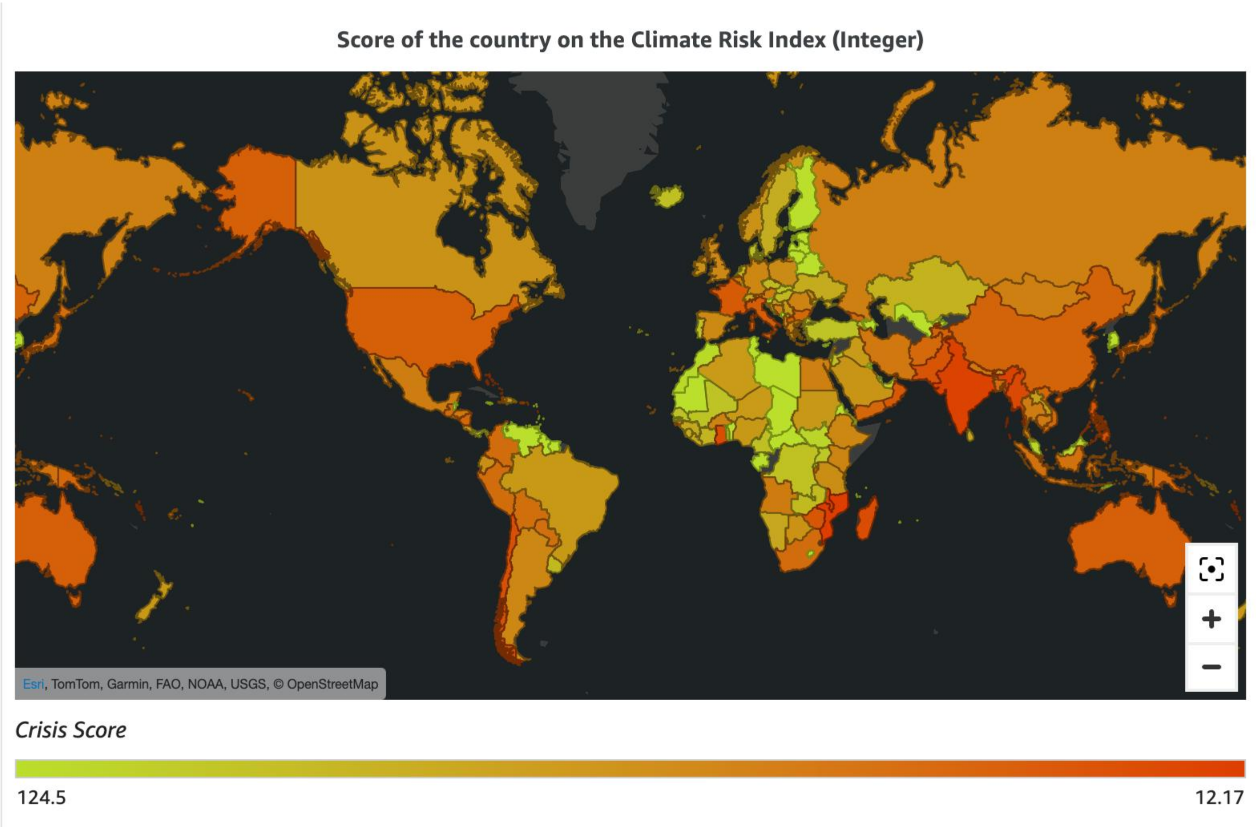

Figure 6. Redesign with Amazon QuickSight: crisis score

This chart shows each country's exposure and vulnerability to climate events. Unlike the original design, which focused solely on thermal stress, the new design visualizes multi-dimensional indices, including storms, floods and droughts, providing a broader and more balanced view of climate risks. Using hierarchical statistical maps with precise profiles can help companies quickly compare weather risks across countries, providing a direct bridge to evidence-based planning and climate finance decisions. At the same time, this data index has both long-term and short-term effects. This is consistent with the principle of fair data, which presents information in a way that is not overly simplified or misleading.

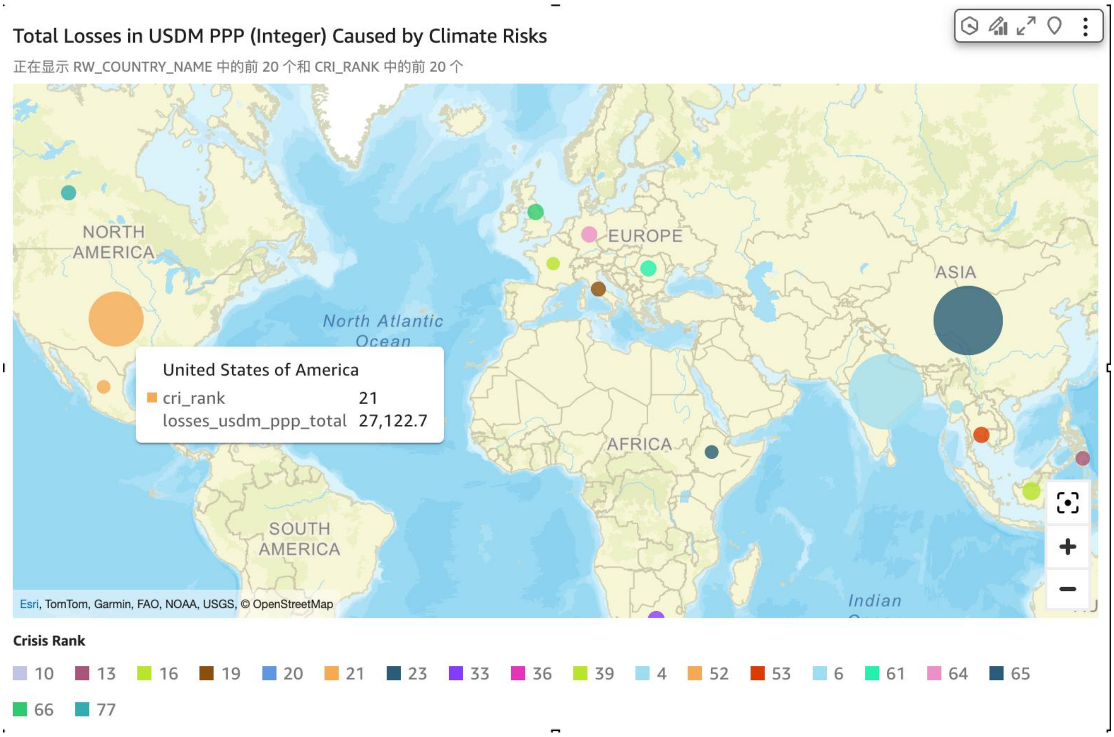

Figure 7. Redesign with Amazon QuickSight: Total number deaths

This chart highlights the top 20 countries with the highest total losses in USDM PPP caused by climate-related events. For example, the United States has a risk ranking of 21, which is relatively high, indicating greater exposure or vulnerability. Its total loss amounts to USD 27.127 billion (approximately USD 27 billion adjusted for purchasing power parity).

The new design uses bubble size to represent the magnitude of economic loss, allowing viewers to instantly identify the regions most affected by climate-related damage. Larger circles naturally draw attention to the most impacted countries without overwhelming the audience. The use of simple bubble shapes reduces the risk of misinterpretation, ensuring high readability and accessibility. The chart is also interactive: when viewers click on a bubble, they can see the specific amount of losses in United States Dollars in Millions (PPP-adjusted) for each country.

Moreover, the metric is clearly defined. It not only complements the previously shown crisis rankings but also helps to reflect each country's vulnerability to natural disasters. The chart avoids technical jargon, making it easier to understand for non-expert and policy-oriented audiences. This aligns well with the principles of data fairness and accessibility.Overall, the updated visualization adheres to design principles of clarity, coherence, and ethical data use, while offering a richer and more comprehensive representation of climate risk. Stakeholders can quickly identify high-risk areas and their associated economic losses, enabling more informed and timely decision-making.

Part 5: Additional flowcharts

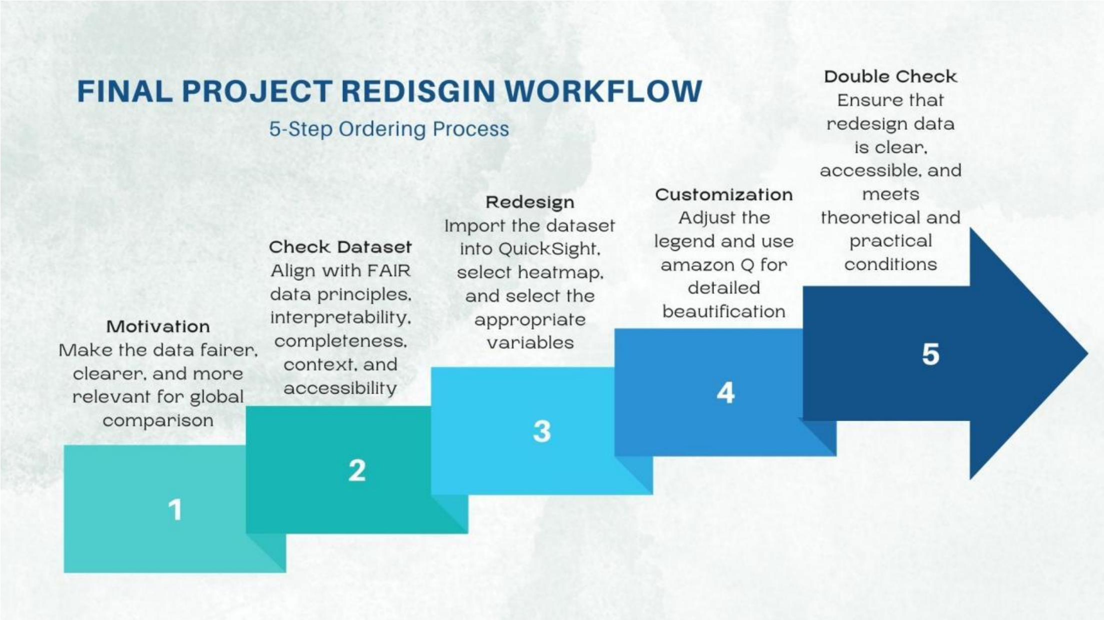

Figure 8. Redesign with Amazon QuickSight: Total number deaths (made by Canva)

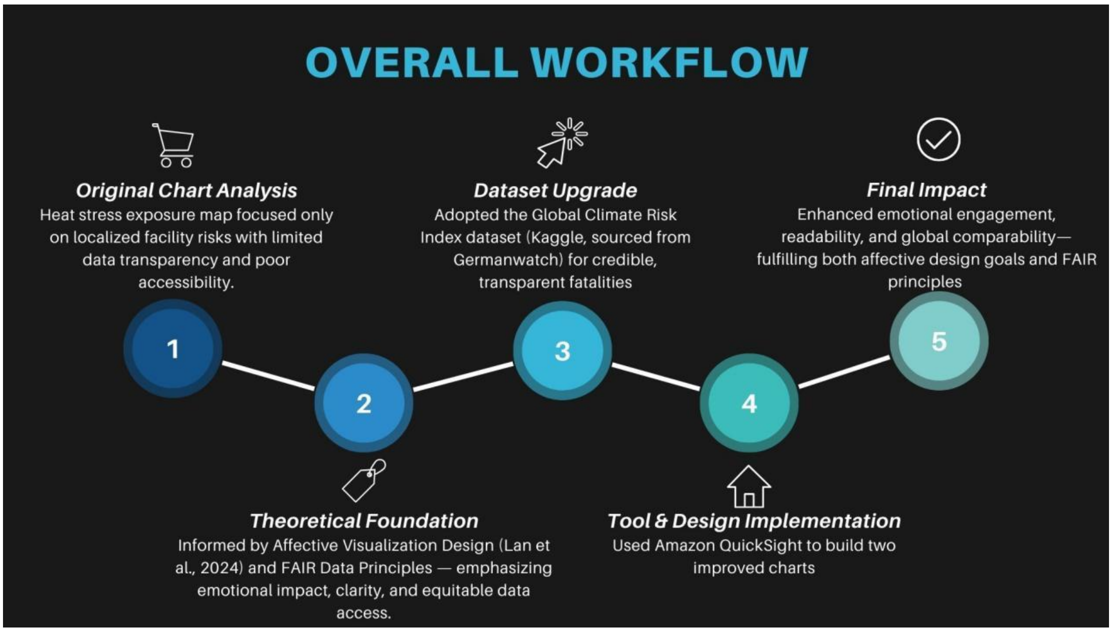

Figure 9. Redesign with Amazon QuickSight: Total number deaths (made by Canva)

Part 6: Github link

https://github.com/PadparadschaNero/Inforsci301

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