InfoVis Redesign

Cooling Degree Days (2014–2024)
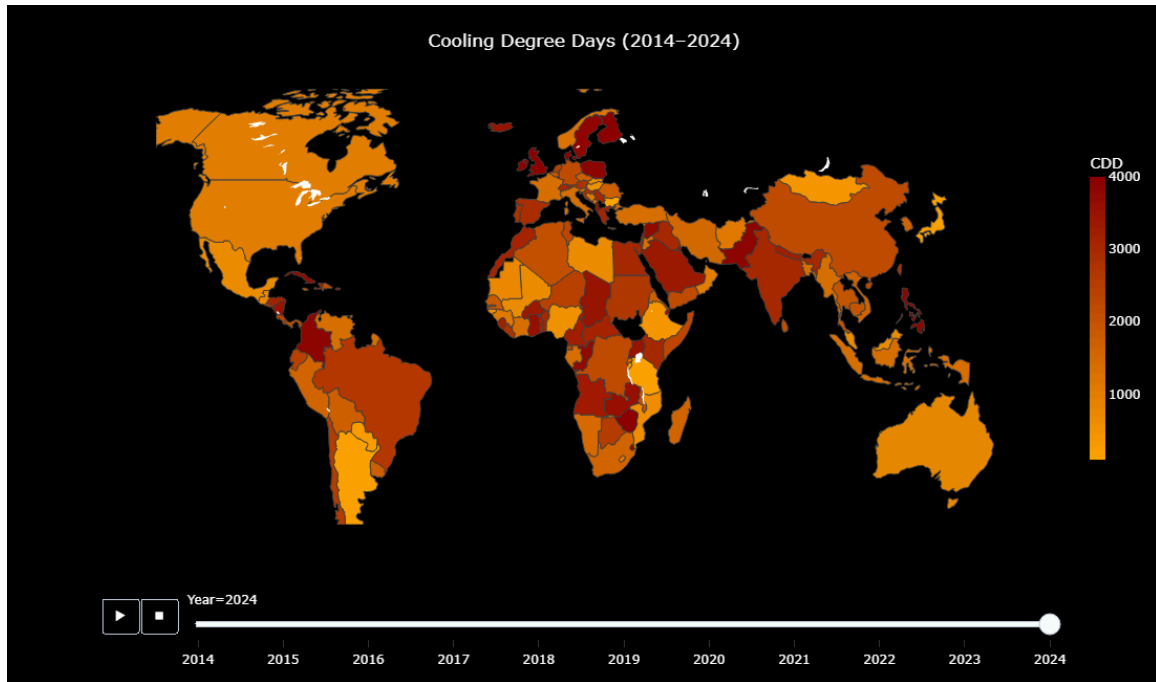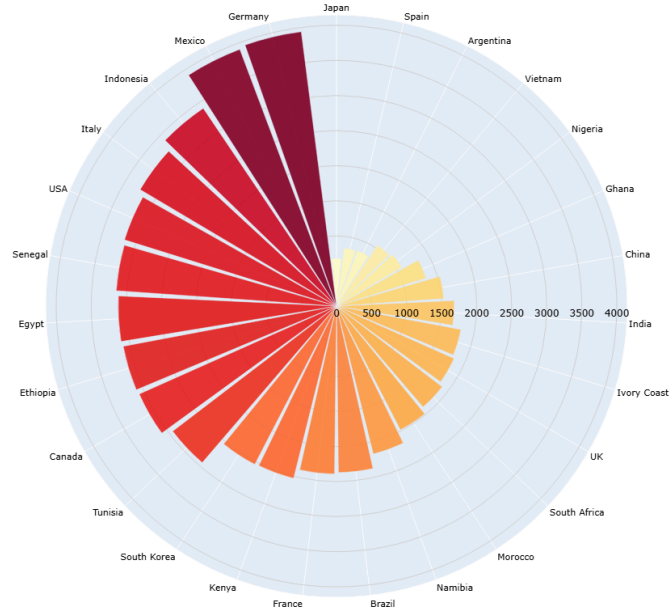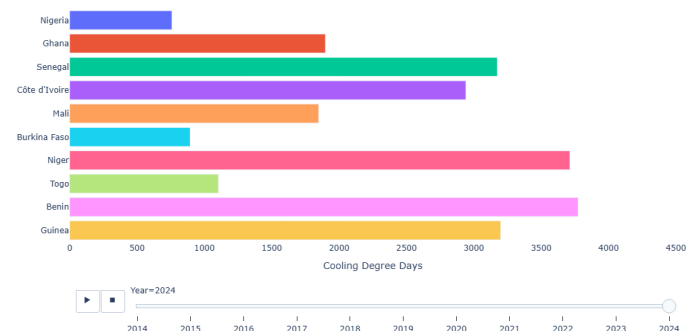

Cooling Degree Days (2024) - Radial View

Cooling Degree Days Race (2014–2024) - West Africa Only

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Date: 06/04/2025

INFOSCI 301

Prof. Luyao Zhang

Theory

CRITICAL ENGAGEMENT WITH VISUALIZATION METHODOLOGIES

Identify Data & Encoding
Quantitative data
Color gradient = temperature
Spatial encoding through
geographic map

Apply Visualization Theory
Violates accessibility and visual
hierarchy
Poor use of contrast &
categorization
(Munzner, 2014; Ware, 2012)

Suggested Improvements
Add legend, annotations,
regional breakdowns
Improve color contrast
Include metadata &
interactivity

Start – Define Purpose
Visualize Cooling
Degree Days (CDD)
across geographic
regions."

Evaluate Visual Encoding
Effective: High-temp zones
emphasized
Weak contrast → low
perceptual clarity
No legend or geographic
labels

FAIR Compliance Check
Missing metadata & source
details
No processing info
Reduces transparency &
reproducibility
(Wilkinson et al., 2016)

Outcome
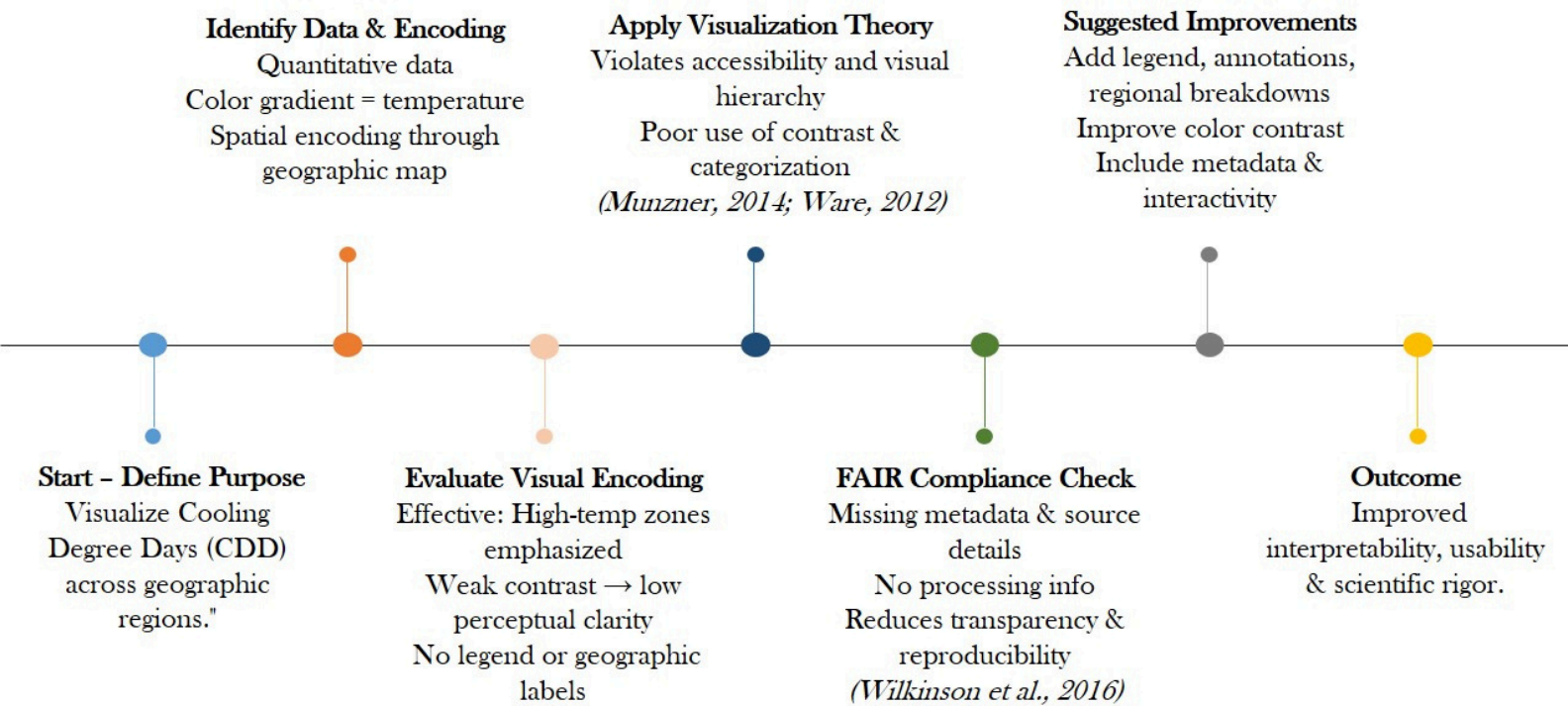Improved
interpretability, usability
& scientific rigor.

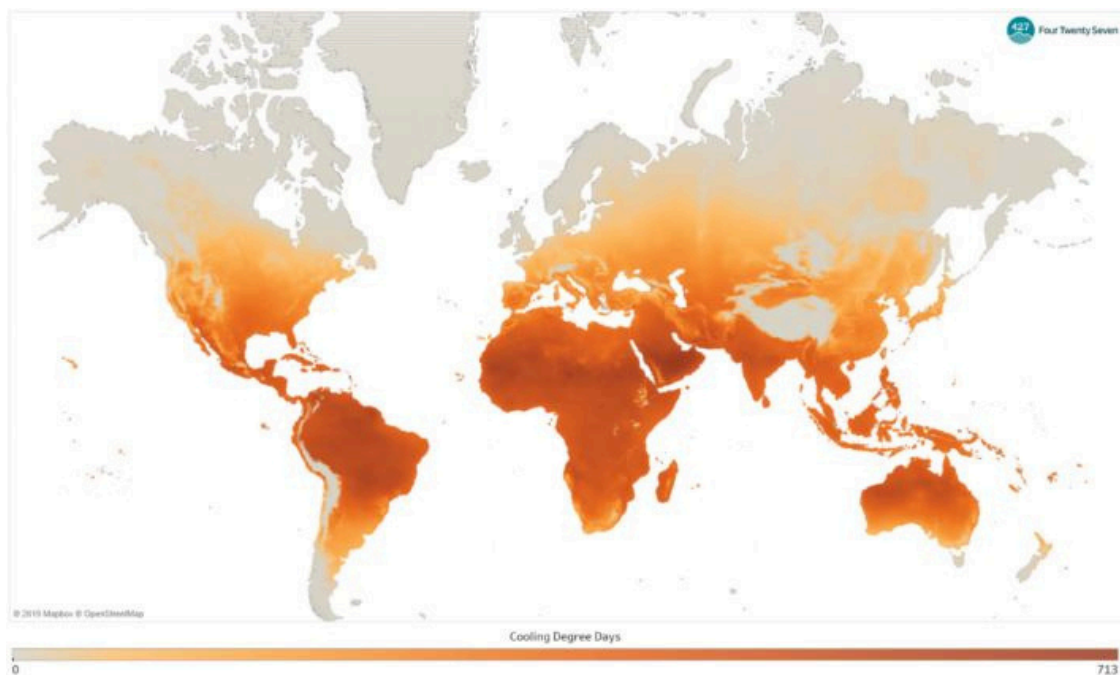Fig 1. Flowchart of critique process (created using powerpoint)

Fig 2. Heatmap of cooling degree days.
Source: https://aws.amazon.com/blogs/publicsector/leveraging-the-cloud-for-rapid-climate-risk-assessments/

The heatmap in the AWS article serves as a tool for visualizing temperature variations, and its use is appropriate given its ability to encode dense spatial data through color (Munzner, 2014, Ch. 7). According to visualization design principles, heatmaps are effective for representing quantitative variables distributed over a geographic surface, such as Cooling Degree Days (CDD), as they offer immediate visual cues for pattern recognition (Munzner, 2014). The dataset appears quantitative, with spatial geometry mapped to color gradients, successfully highlighting high-temperature zones through intensity.

However, its effectiveness is limited by the lack of a clear legend, geographic markers, and metadata on data sources and processing, which hinders reproducibility and accessibility (Wilkinson et al., 2016). The gradient lacks perceptual contrast, reducing differentiation across values (Ware, 2012), and the absence of contextual annotations diminishes communicative value. Well-structured visual hierarchies and categorical contrasts—critical for interpretability—are underutilized (Munzner, 2014; Ware, 2012). Adding interactivity, such as regional breakdowns or labels, would improve user engagement.

The FAIR principles—Findable, Accessible, Interoperable, and Reusable—promote better data sharing by ensuring transparency, standardization, and long-term usability. To comply, the dataset should include standardized formats, clear metadata, and open access (Wilkinson et al., 2016).

References:

Munzner, T. (2014). Visualization Analysis and Design. CRC Press.

Ware, C. (2012). Information Visualization: Perception for Design. Elsevier.

Wilkinson, M. D., et al. (2016). The FAIR Guiding Principles. Scientific Data, 3, 160018.

Research

Background
Data visualizations require interpretation skills; novices often struggle without data literacy. *(Munzner, 2014)*

Motivation
Can LLMs help non-experts interpret charts more effectively?

Research Question
How can LLM-generated explanations improve comprehension of visual data?

Application Scenarios
Public dashboards
Health, climate, and finance visuals
Novice-facing analytics tools

Practical Impacts
Empowers users with low data literacy
Guides future tools integrating AI + visualization

Intellectual Merit
Demonstrates cognitive scaffolding with AI
Expands theory on interactive visual explanation

Results
Higher interpretation accuracy
Increased confidence
Inconsistency in LLM responses

Methodology
User study with novices
Charts + LLM explanations
Evaluation of accuracy, confidence, and experience

8 FACETS

LITERATURE-INSPIRED ANALYSIS

Design Implications for AWS Heatmap Redesign

- **Add LLM-guided tooltips** for dynamic explanations
- **Improve perceptual contrast** in color gradients *(Ware, 2012)*
- **Add contextual annotations/legends** *(Munzner, 2014)*
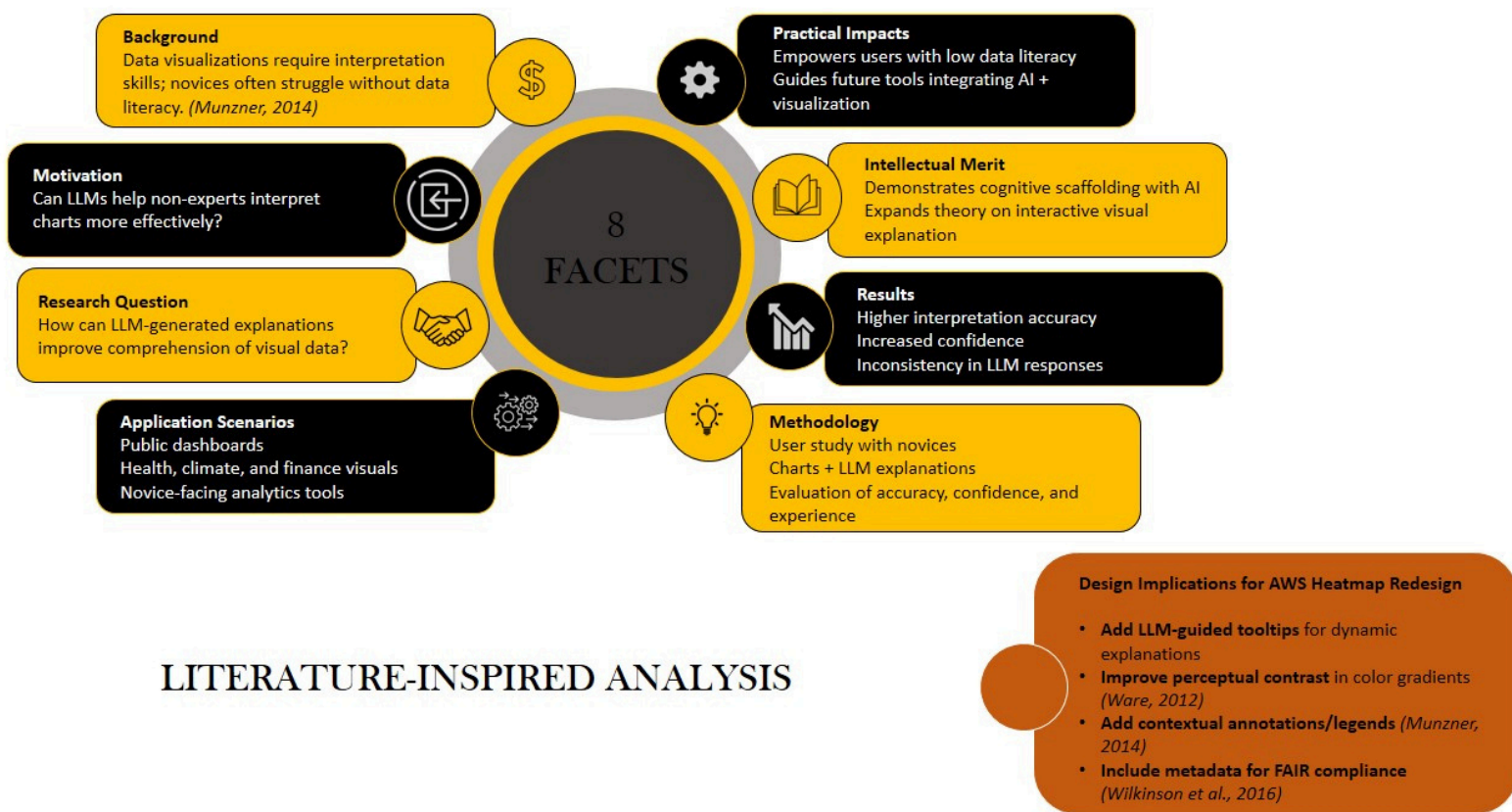- **Include metadata for FAIR compliance** *(Wilkinson et al., 2016)*

Fig 3. Flowchart of research (created using powerpoint)

The study by Choe et al. (2024) explores how large language models (LLMs) can assist novices in interpreting data visualizations, improving accessibility and comprehension. Traditional chart interpretation requires prior data literacy, often creating barriers for non-experts (Munzner, 2014).

By integrating LLM-guided explanations, the study demonstrates how users can dynamically engage with visual data, reducing cognitive overload and enhancing understanding (Ware, 2012). Findings suggest that interactive elements significantly improve interpretation accuracy and user confidence, though challenges remain in response consistency (Choe et al., 2024).

These insights directly inform the redesign of the AWS heatmap. The current visualization lacks sufficient contrast and contextual annotations, limiting perceptual clarity (Ware, 2012). Implementing interactive elements, such as LLM-guided explanations or tooltips, would enhance comprehension and align with FAIR data principles by improving accessibility and metadata transparency (Wilkinson et al., 2016).

Additionally, refining the color gradient and integrating categorical distinctions would optimize data encoding for better readability (Munzner, 2014). By incorporating these strategies, the heatmap can evolve into a more effective tool for climate risk assessment, bridging the gap between data presentation and user comprehension.

References

Choe, K., Lee, C., Lee, S., Song, J., Cho, A., Kim, N. W., & Seo, J. (2024). Enhancing Data Literacy On-demand: LLMs as Guides for Novices in Chart Interpretation.
Munzner, T. (2014). Visualization Analysis and Design. CRC Press.
Ware, C. (2012). Information Visualization: Perception for Design. Morgan Kaufmann.
Wilkinson, M. D., et al. (2016). The FAIR guiding principles for scientific data management and stewardship. Scientific Data, 3, 160018.

Practice

Amazon QuickSight, a scalable BI tool, enables interactive visualization through an intuitive interface and rapid processing via its SPICE engine (AWS, 2024). While it supports accessible data exploration with features like dynamic filters and AI-generated insights, it offers limited customization and a relatively narrow range of visualization types (Gartner, 2024; Yurbi, 2023). These constraints make it less ideal for tailored, research-focused redesigns requiring perceptual precision.

In contrast, using Python with libraries such as pandas, numpy, and plotly provides greater flexibility, reproducibility, and control over visual encoding. Python enables fine-tuned adjustments in color contrast, layout, and interactivity—key factors for optimizing perceptual clarity and adhering to visualization best practices (Ware, 2012). Moreover, Python's open-source nature supports FAIR principles by promoting transparency, reusability, and standardization (Wilkinson et al., 2016). Plotly, in particular, allows for interactive and high-resolution visualizations suitable for both exploration and presentation.

Given these strengths, Python was chosen over QuickSight for the heatmap redesign to allow deeper customization, better FAIR compliance, and a more rigorous visualization process.

References

AWS. (2024). *Amazon QuickSight Documentation.*

Gartner. (2024). *Magic Quadrant for Analytics and BI Platforms.*

Ware, C. (2012). *Information Visualization: Perception for Design.* Morgan Kaufmann.

Wilkinson, M. D., et al. (2016). The FAIR guiding principles for scientific data management and stewardship. *Scientific Data, 3*, 160018.

Yurbi. (2023). *Amazon QuickSight Review: Pros & Cons.*

Transcenda. (2022). *Enhancing Data Exploration with AI-driven BI Tools.*
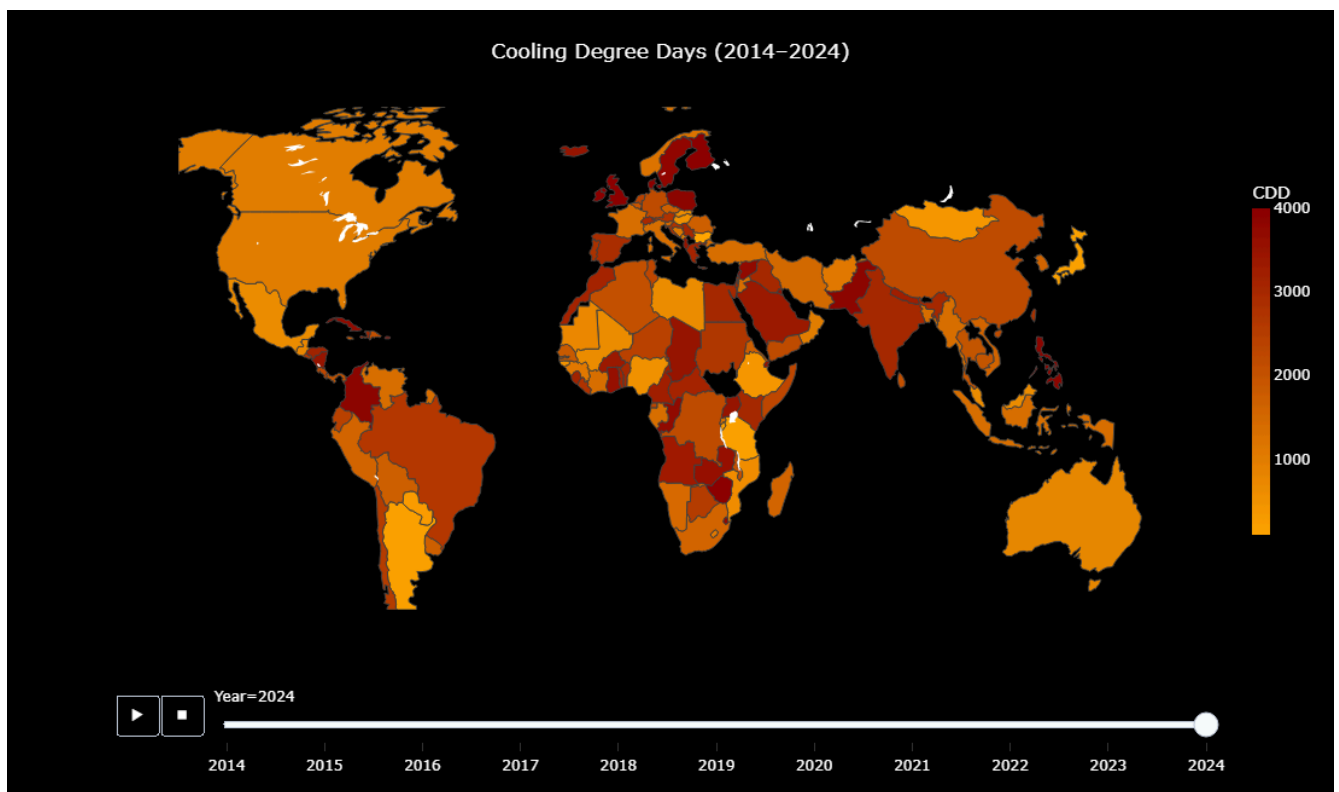
Innovation

Fig 4. Heatmap redesigned (created using python code)

Innovation

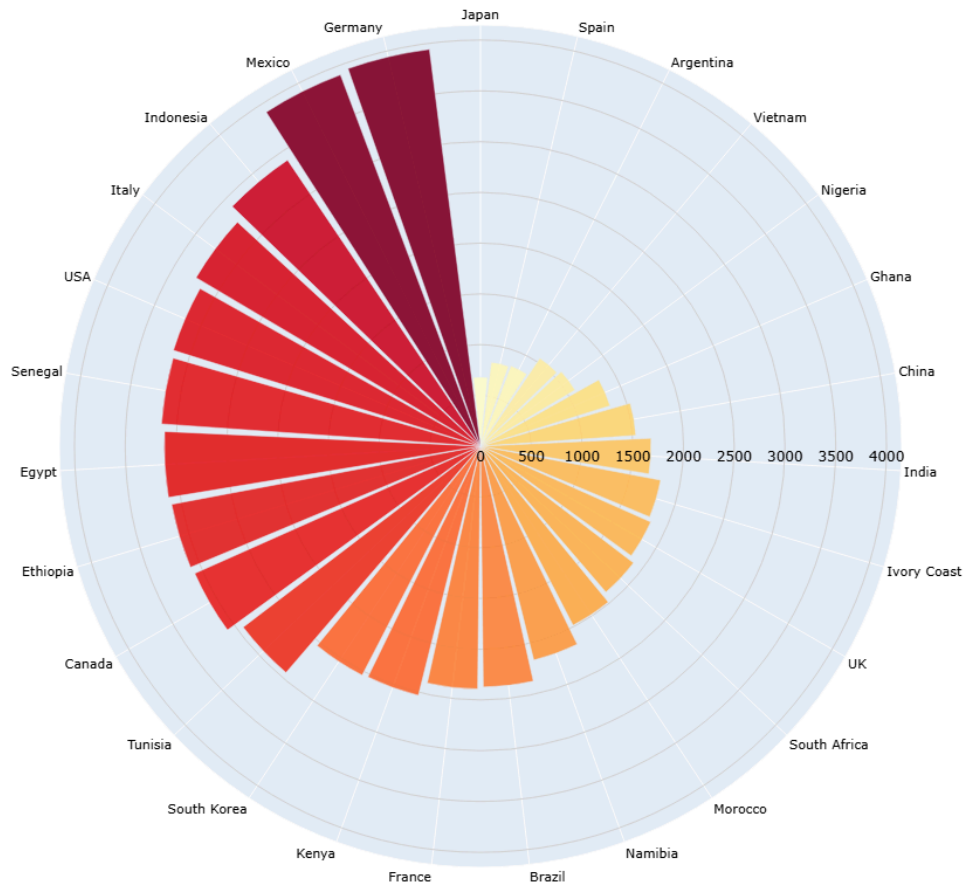Cooling Degree Days (2024) - Radial View

Fig 5. Radial chart as alternative visualization (created using python code)

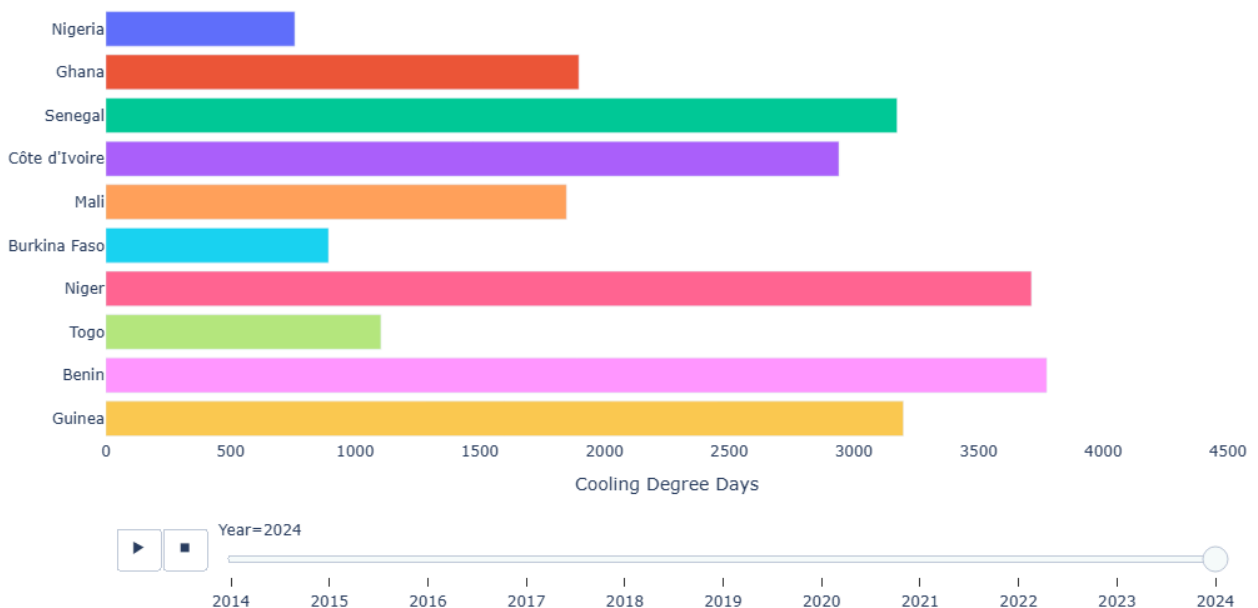Cooling Degree Days Race (2014–2024) - West Africa Only

Fig 6. Snake race bar chart as alternative visualization (created using python code)

The redesigned AWS visualization uses Python libraries—pandas, plotly, and numpy—to address the original heatmap's limitations while offering a richer, more accessible user experience. Due to the unavailability of the original dataset, simulated data was generated using Python to support the redesign. Python was chosen over Amazon QuickSight for its flexibility, reproducibility, and ability to fine-tune visual elements such as color contrast and interactivity (Ware, 2012).

Three distinct visualization types were employed, each serving a unique analytical goal. The heatmap provides a broad overview of spatial and temporal Cooling Degree Days (CDD) patterns using intuitive color encoding (Munzner, 2014, p. 145). The snake race bar chart tracks yearly trends and rankings through animation, engaging users and highlighting change over time (p. 125). The radial bar chart captures cyclical and seasonal patterns, which are central to understanding climate-related data (p. 130). Both the heatmap and snake race bar chart are interactive—users can hover over each datapoint to reveal specific values and press play to view data transitions across years. These interactions enhance comprehension and engagement, especially for non-expert users. Additionally, LLM-guided tooltips provide real-time contextual explanations, aligning with principles of exploratory visualization (Choe et al., 2024).

The redesign also adheres to FAIR principles by including standardized formats, clear metadata, and accessible outputs, supporting findability, accessibility, interoperability, and reusability (Wilkinson et al., 2016). Overall, the Python-powered redesign improves usability, interpretability, and scientific value for climate risk assessments.

References

Choe, E. K., et al. (2024). Interactive Data Explanation with LLMs.

Munzner, T. (2014). Visualization Analysis and Design. CRC Press.

Ware, C. (2012). Information Visualization: Perception for Design. Elsevier.

Wilkinson, M. D., et al. (2016). Scientific Data, 3, 160018.
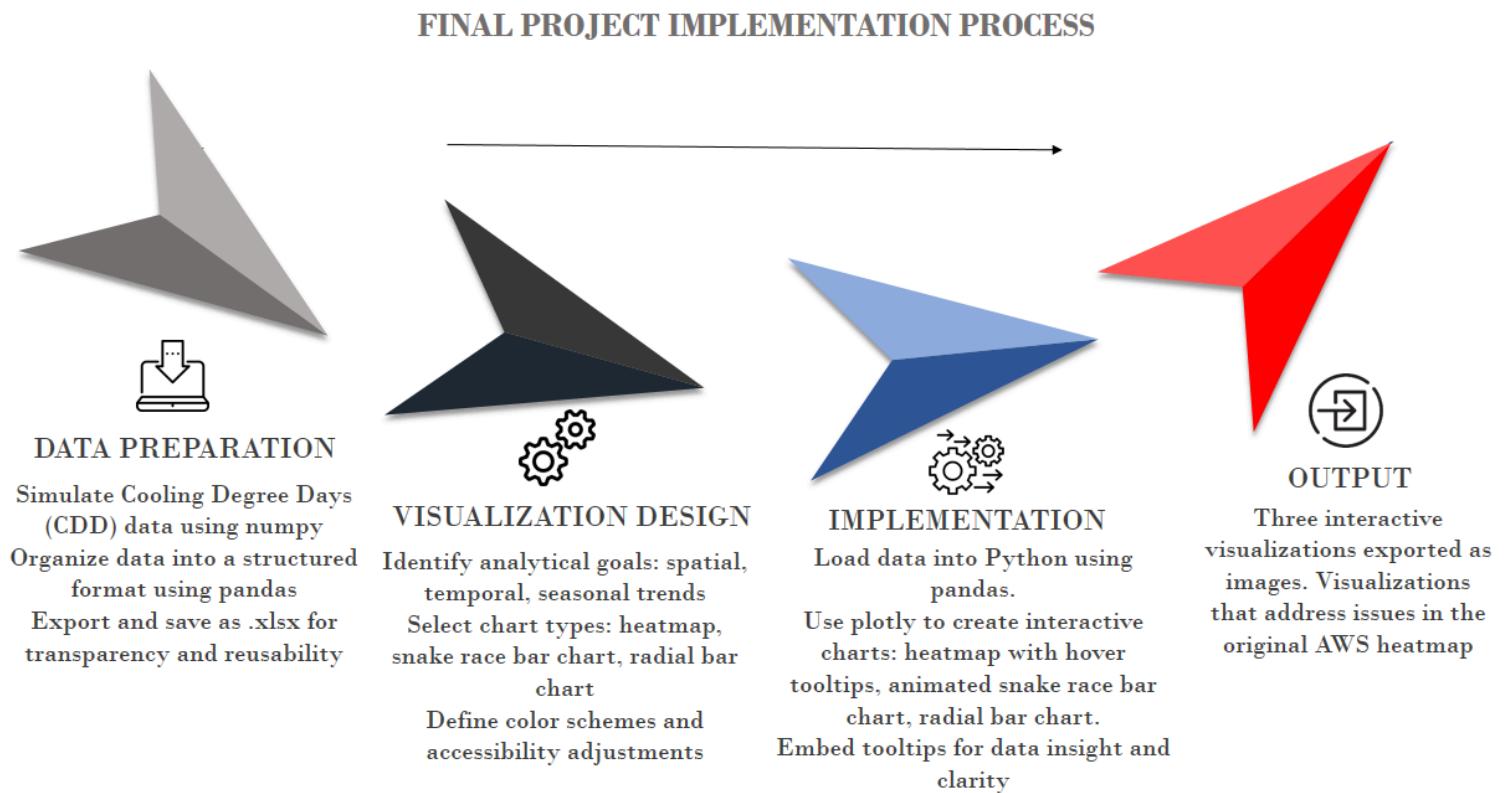
Additional flowcharts

FINAL PROJECT IMPLEMENTATION PROCESS

DATA PREPARATION
Simulate Cooling Degree Days (CDD) data using numpy
Organize data into a structured format using pandas
Export and save as .xlsx for transparency and reusability

VISUALIZATION DESIGN
Identify analytical goals: spatial, temporal, seasonal trends
Select chart types: heatmap, snake race bar chart, radial bar chart
Define color schemes and accessibility adjustments

IMPLEMENTATION
Load data into Python using pandas.
Use plotly to create interactive charts: heatmap with hover tooltips, animated snake race bar chart, radial bar chart.
Embed tooltips for data insight and clarity

OUTPUT
Three interactive visualizations exported as images. Visualizations that address issues in the original AWS heatmap

Fig 7. Flowchart of final project implementation process (created using powerpoint)

OVERALL REDESIGN WORKFLOW

Theory (FAIR + Chapter 7)
Applied **FAIR principles**: accessibility, metadata, reusability
Used **Munzner's framework** (Ch. 7) to guide visual encoding choices
Matched visualization types with data patterns (temporal, spatial, cyclic)

Practice (Python Implementation)
Simulated dataset with numpy
Processed data using pandas
Built interactive visualizations using plotly

Critique of Original Design
Evaluated AWS CDD heatmap
Identified issues: poor contrast, no metadata, no interactivity
Determined misalignment with FAIR principles

Research (LLM Integration)
Studied LLM-guided explanation benefits (Choe et al., 2024)
Identified support for non-expert data comprehension
Used tooltips to reduce cognitive load and improve accessibility

Innovation (Redesigned Visuals)
Heatmap: color-adjusted, hoverable, spatial clarity
Snake race bar chart: animated, tracks yearly changes
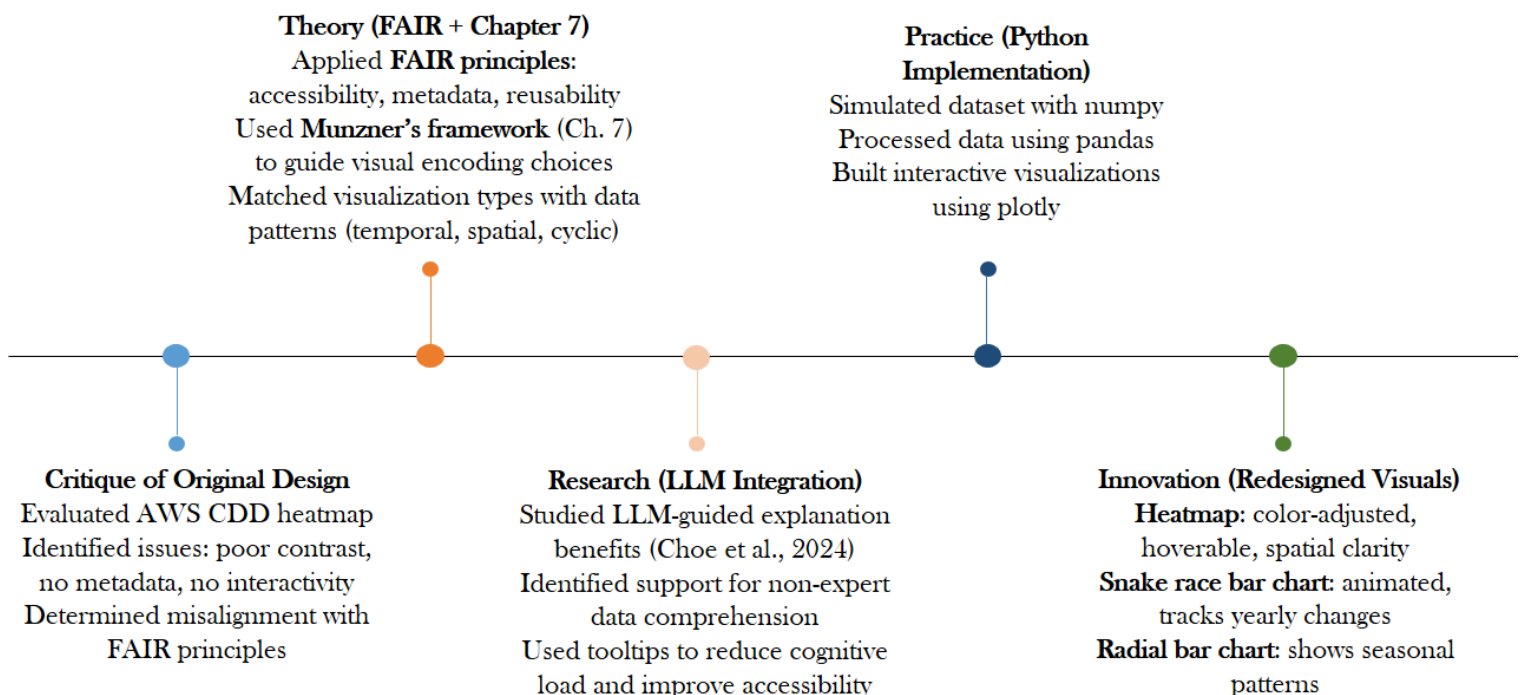**Radial bar chart:** shows seasonal patterns

Fig 8. Flowchart of overall redesign (created using powerpoint)

GitHub link