Community Resilience Analysis Library

This document provides a compact overview of the Community Resilience Analysis Library — a Python-based toolkit designed to evaluate community recovery following disasters using mobility data. GitHub: https://github.com/amarnath-reddy-0-9-1-2/Resilience/

1. Project Overview

The library helps researchers and analysts quantify and visualize how communities recover from disasters using human mobility data. It supports two key models — the Resilience Triangle Model and the Area Under the Curve (AUC) Model — to measure the speed and quality of recovery over time.

2. Disaster Context

The primary dataset used is `portarthur_sd_df_2019.rdata`, focusing on Port Arthur, Texas. The analysis centers around Tropical Storm Imelda, which impacted the region between September 17 and September 27, 2019.

3. Key Models & Functionality

- The library implements two core models:
  - Resilience Triangle Model – Measures how quickly a community returns to pre-disaster conditions, calculating both recovery speed and depth.
  - Area Under the Curve (AUC) Model – Quantifies total impact by calculating area-based loss and recovery over time.
- Main functionalities include:
  - Data Preparation – Load and preprocess SafeGraph mobility data.
  - Resilience Metrics Calculation – Automatically compute key recovery indicators.
  - Visualization – Generate plots to illustrate resilience and recovery trends.
  - Batch Processing – Run resilience analysis across all CBGs and export results to CSV.

4. References

[1] Hong, H., Liu, L., Peng, Z.-R., & Li, W. (2021). *Measuring inequality in community resilience to natural disasters using large-scale mobility data*. Nature Communications, 12(1), 1870. https://doi.org/10.1038/s41467-021-22177-2

[2] Chen, K., Hu, S., Hong, H., & Peng, Z.-R. (2024). *Community resilience to wildfires: A network analysis approach by utilizing human mobility data*. Computers, Environment and Urban Systems, 104, 102032. https://doi.org/10.1016/j.compenvurbsys.2023.102032

5. Folder Structure

Folder/File	Detailed Description
data/	Contains the raw mobility data files required for analysis. Example: • \`portarthur_sd_df_2019.rdata\`, which stores SafeGraph mobility data for Port Arthur. • \`tl_2019_48_bg.zip\` has geographic data of the Texas region.
models/	Includes core implementation of resilience models: • \`resilience_auc.py\`: Implements the Area Under Curve (AUC) model to calculate the area loss and recovery after a disaster. • \`resilience_triangle.py\`: Implements the Resilience Triangle model to measure loss and recovery using geometric triangle-based methods.
notebooks/	Interactive Jupyter notebooks to test and debug the model logic: • \`mobility_patterns.ipynb\`: Analyzes mobility data trends across various granularities. • \`resilience_auc.ipynb\`: Runs and visualizes AUC model for a specific Census Block Group (CBG). • \`resilience_triangle.ipynb\`: Executes and visualizes Triangle model for a specific CBG. • \`geographic_patterns.ipynb\`: This will generate geographic maps based on the data.
run_examples/	Standalone example scripts to run models easily: • \`batch_processing.py\`: Applies the Triangle model to all CBGs and outputs a summary CSV. • \`run_auc_example.py\`: Demonstrates running the AUC model for one CBG. • \`run_triangle_example.py\`: Demonstrates running the Triangle model for one CBG.
visualization/	Functions to create visual and textual output: • \`graph_visualization.py\`: Plots mobility and resilience curves for each region. • \`log_visualizations.py\`: Logs model metrics in a human-readable, well-formatted way.
utils.py	General-purpose utility functions used across the project. Includes helpers for smoothing, normalization, and date handling.
data_processing.py	Responsible for loading, cleaning, and preprocessing SafeGraph mobility data. Prepares the dataset for modeling.
results/	Stores all generated outputs: CSV results, resilience patterns, geo patterns, mobility patterns from model runs. Used to review or share analysis findings. More explanation in the results section.

6. Results and Analysis

The images and the CSV files are available in the results folder.

1. All the CBG results are available in the cbg_resilience_summary.csv file.
2. Filtered CBGs that show a clear trend are stored in cbg_resilience_summary_filtered.csv.
3. The 'resilience_patterns' folder contains visualizations for one individual CBG using both models.
4. The 'mobility_patterns' folder contains overall mobility patterns at different levels.
5. The 'geo_patterns' folder contains the geographic plots based on the model data on the map.
6. The 'network_patterns' folder contains the patterns based on the given data using networkx.

Key Findings

1. Out of 309 CBGs, around 222 CBGs showed a clear trend for Hurricane Imelda.
2. The results are sensitive to hyperparameters such as:
   - Baseline value
   - Smoothing period
   - Disaster timeline (some CBGs showed trends slightly after the disaster period)
3. Consistent Dip During Disaster (Sep 17–27, 2019):
   All regions (CBGs/counties) show a sharp decline in inflow or in-degree, confirming disruption in daily mobility.
4. Varying Recovery Patterns Across Regions:
   - Jefferson County shows faster recovery, indicating stronger resilience.
   - Orange and Jeff Davis Counties show delayed/weaker recovery, indicating lower resilience.
5. Resilience Triangle Area Reflects Recovery Efficiency:
   - Smaller triangle area → quicker mobility recovery and higher resilience.
   - Larger triangle area → prolonged disruption and lower resilience.
6. Aggregated Trends Mask Local Disparities:
   - Metro-level aggregation hides local variations.
   - CBG-level plots reveal specific mobility dynamics and localized recovery trends.
7. Pre-Disaster Baseline is Crucial:
   - Calculated as 2-month average before disaster.
   - Enables identification of dip (tD) and recovery (t1) points.
8. Summary Statistics:
   - Average Resilience: 13.82% , Average Robustness: 0.004522, Average Vulnerability: 0.004264