Appendix A- Methods

Accessibility modelling

Urban accessibility under flood conditions was assessed using spatial configuration metrics from Space Syntax theory, applied at two radii (r3000 and r800) to represent global and local scales respectively. A 100-year return period flood model (OpenCity Data) was used to impose penalties on street network segments based on inundation severity. Segments were either removed (100% penalty) or penalized by 75% or 25% depending on depth. The analysis was implemented using the Space Syntax Toolkit plugin in QGIS.

Flood impact was incorporated using a multiplicative penalty applied to baseline accessibility values as follows:

$$A\_flooded = A\_base \times (1 - p)$$

Where:

- A_base is the original accessibility value (NAIN or NACH),
- p is the penalty factor (1.0 for full removal, 0.75 or 0.25 for moderate or low disruption),
- A_flooded is the resulting accessibility score under flood conditions.

Network preparation and overlay

The base road network was sourced from OpenStreetMap and manually filtered. Shelter locations, boat access points, and population density figures were extracted from PDFs in the Greater Chennai Corporation's City Disaster Management Perspective Plan (2024) and digitized in QGIS. Supplementary hydrological features were obtained from IWRS datasets and enhanced with hand-mapped canals from satellite imagery. Historical land use maps were redrawn from Greater Chennai planning documents and georeferenced.

Data processing and land use classification

Land use categories were extracted using image segmentation in Python (OpenCV and shapely). Resulting vectors were spatially matched to urban blocks using geopandas and pandas. These enriched geometries served as a base for accessibility overlay and clustering.

Clustering analysis

K-means clustering (SPSS) was applied to flood-free blocks using three normalized variables: population density, NAINr800, and NAINr3000. Min-max normalization was used:

$$\text{Normalized Value} = (X - X\_min) / (X\_max - X\_min)$$

After iterative testing, 10 clusters were selected. Five-cluster solutions lacked spatial and accessibility diversity, while higher numbers produced fragmented patterns. Clusters 7 and 9 were identified as high-priority zones.

Additional considerations

Several datasets were reviewed but not incorporated into the final model. These included flood scenarios with 10- and 50-year return periods, maps of streets affected during the 2015 and 2020 flood events, and the locations of meteorological stations. These layers were used during the exploratory phase to contextualize exposure patterns and assess the robustness of the 100-year flood model. The decision to focus solely on the 100-year return period aligns with common standards in hydraulic infrastructure planning, where such models are used to represent low-probability, high-impact events relevant for long-term resilience.

Software summary

- QGIS 3.28 with Space Syntax Toolkit plugin
- Python with OpenCV, shapely, geopandas, pandas
- SPSS for statistical clustering

Data sources

- OpenStreetMap: Base Road network
- OpenCity Data: 100-year flood model
- Greater Chennai Corporation (2024): Population, shelters, boats (digitized from PDFs)
- IWRS (India): Water network reference
- Satellite imagery: Canal mapping
- Historical land use maps (PDF, Greater Chennai Corporation): Redrawn and georeferenced