2.3. Superblockify Analysis

To assess the potential of superblocks in enhancing bicycle safety, we begin by identifying candidate areas for superblock implementation based on their existing traffic patterns and bicycle crash rates. Superblocks restrict through-traffic within designated zones, which enables a physical separation between cyclists and motor vehicles– a key factor in reducing bicycle-vehicle crash rates. By comparing the traffic patterns in our diffusion model (Figure 8B) with the spatial distribution of bicycle crash rates (Figure 9A), we identified the Upper East Side and Midtown as the most likely to benefit from superblock implementation due to their combination of high traffic volumes and elevated crash rates. Based on these findings, we use the Python package *Superblockify* ((Büth, Vybornova, and Szell 2024)) to generate potential superblock configurations in our target neighborhoods, which we then evaluate for their effectiveness in improving bicycle safety and suitability in their neighborhoods.

2.3.1. Approach

Realistic superblock implementation requires careful consideration of both the potential benefits and unintended harms to the surrounding neighborhood. We predict the impact of implementation on the street network's accessibility and connectivity as well as the neighborhood's social compatibility with a superblock, including land use, residential composition, and business activity. Ultimately, we synthesize this information to identify superblocks that maximize benefits while minimizing disruption.

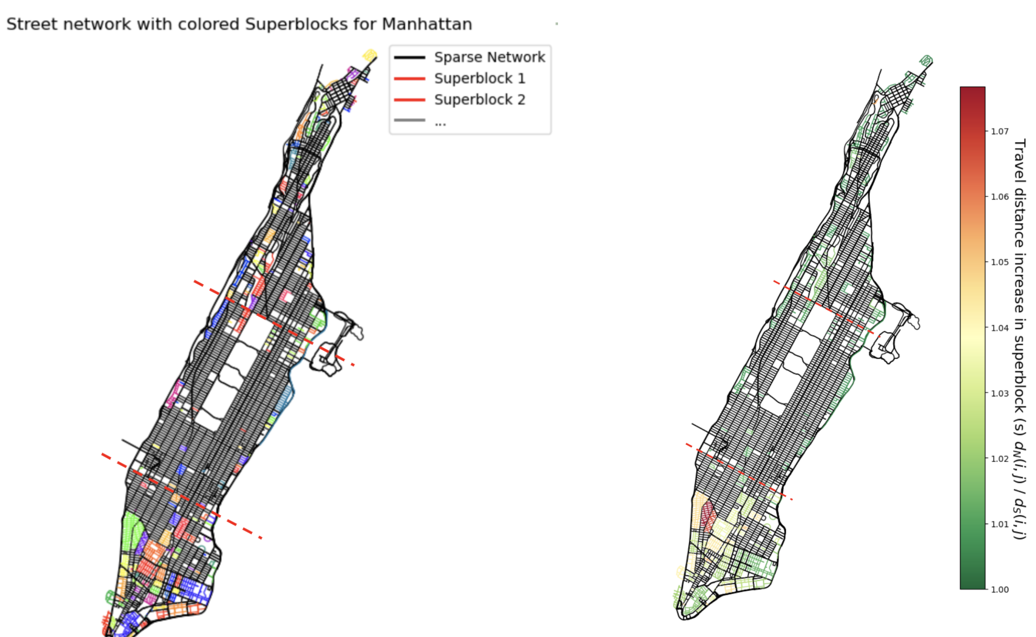
For superblock candidate identification, we used the Python package *Superblockify*, which partitions street networks into superblocks using spatial and population data from OpenStreetMap and Global Human Settlement, respectively. For our study, we utilize the `ResidentialPartitioner` to partition streets in Manhattan with a residential street tag. This will remove high-importance roads (such as motorways) and only partition roads with access to residential housing. The *Superblockify* partitioner output includes superblock candidate boundaries along with associated metrics such as distance calculations; additional metrics, including betweenness centrality, can also be computed using *Superblockify*.

Superblockify finds the shortest-path distance between every point on the graph before and after superblock implementation using a restricted distance calculation. They define the percent increase in travel distance caused by each superblock as the fraction of the two distances. This shows us the level of traffic disruption caused by each superblock, a metric we hope to minimize. Further, *superblockify*'s `betweenness_centrality` function calculates how frequently nodes and edges lie on shortest paths. Nodes and edges correspond to intersections and road segments, respectively; hence, this metric indicates how critical an intersection or street is for connecting the overall street network.

Superblockify's metrics focus on the impact superblock implementation has on vehicles, but we also want to ensure they improve a biker's ability to safely navigate the city. Since the internal streets of a superblock are designated pedestrian and cyclist spaces, these streets expand the designated bicycle lane network. While cyclists are permitted to share streets with cars even without designated lanes, we consider such conditions unsafe for bikers. So, we apply the same betweenness centrality metric to assess how each superblock affects the bicycle network, intending to add new, strategically important lanes to improve connectivity.

Additionally, we evaluate the social characteristics of the neighborhood by compiling data from OSM on residential composition, business types, and land use to assess its suitability for a pedestrian- and cyclist-oriented superblock. While this provides a useful overview, it represents only a preliminary analysis and may not fully capture all social dynamics or economic effects. Future work could incorporate community engagement, further demographic trends, and an economic assessment to support a more comprehensive evaluation.

Finally, we analyze each superblock candidate generated by *superblockify* and evaluate how well it aligns with our goals. By considering network connectivity and social compatibility, we select the superblocks that most effectively enhance bicycle transportation and minimize disruption.



A. Superblock candidates

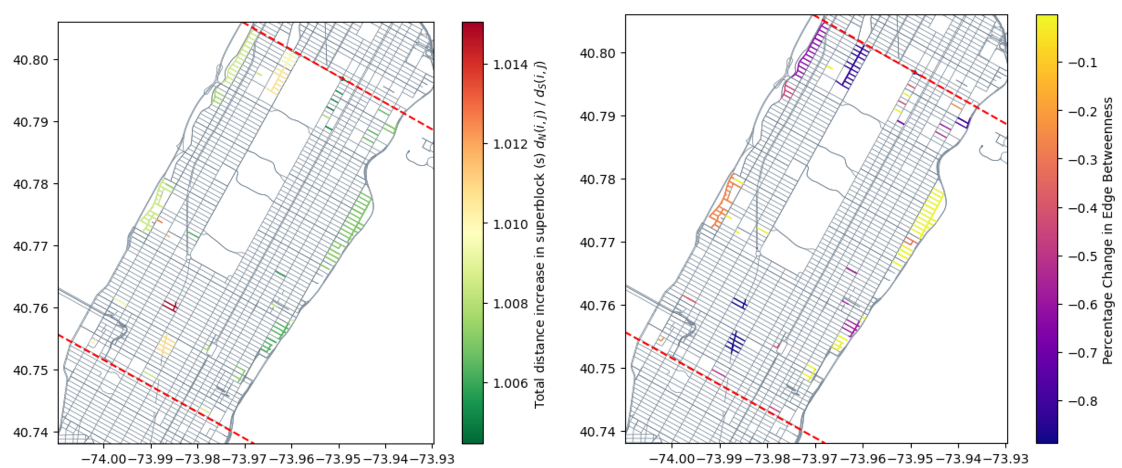
B. Relative increase in travel distance

FIGURE 1. *Superblockify* partitioning output

2.3.2. Results

The superblock candidates generated by *Superblockify*'s partitioner for the search string "Manhattan, Manhattan County, New York, United States" are visualized in the *Superblockify* generated plot in Figure 1A. The red dashed lines along 110th st and 30th st indicate the boundaries of our target area: we will only evaluate the candidates located fully within these boundaries. This leaves us with 42 superblocks to evaluate.

We incorporated two methods to analyze the effect of these candidates on traffic flow. The first is by evaluating the local impact of each superblock's implementation using travel distances as summarized in Figure 1B generated by *Superblockify*. We reproduced this plot in Figure 2A to analyze the variation in distance increase in just our target area. All of our superblocks cause a less than 1.5% increase in travel time distance, indicating a low level of local disruption. The second method uses changes in edge betweenness centrality as an indicator of how much traffic must be rerouted after superblock implementation. To assess network disruption, we categorized changes in edge betweenness centrality into four levels: low (> –0.25), moderate (–0.25 to –0.45), high (–0.45 to –0.65), and very high (< –0.65). Greater negative values indicate more substantial traffic rerouting and potential network instability; hence, superblocks with low and moderate edge betweenness changes are ideal for our goals.

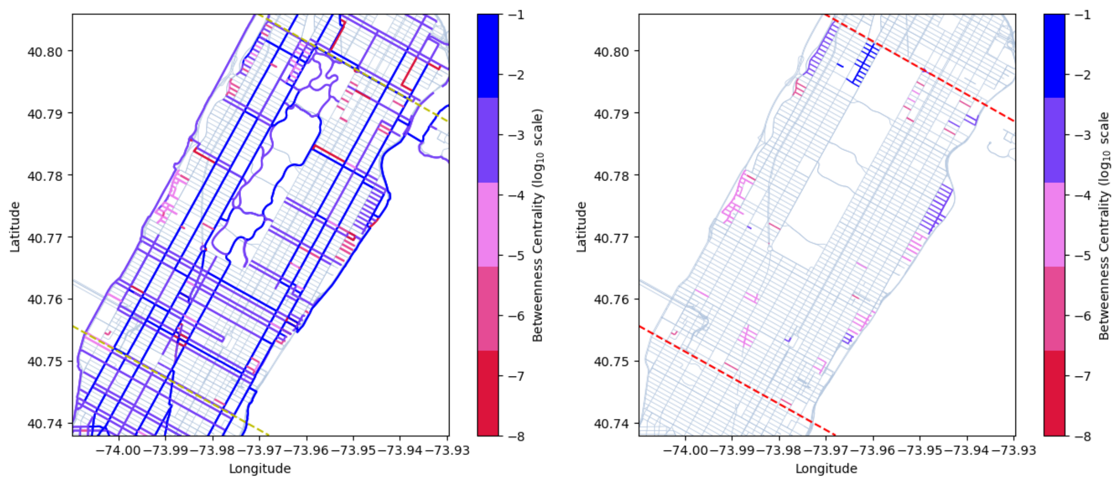


A. Relative Distance Increase

B. Edge Betweenness Percent Decrease

FIGURE 2. Relative Network Disruption Across Superblocks

We use edge betweenness once again to assess the impact of expanding the bicycle network with superblocks. Here, we focus on the edge betweenness centrality after superblock implementation and want to find the candidates that add important routes to the network. To mitigate the influence of extreme values in the edge betweenness distribution, we used a logarithm-transformed betweenness in Figures 3A and 3B. This provides a more balanced representation of a superblock's importance to the overall bicycle network connectivity. To assess the importance of each superblock, we categorized the log-transformed edge betweenness centrality into four levels: low (< –7), moderate (–7 to –5), high (–5 to –3), and very high (> –3). Since values are log-transformed, greater numbers indicate greater importance within the network; hence, superblocks with high and very high log-transformed edge betweenness are ideal for our goals.



A. Designated Bike Routes and Superblocks

B. Values Averaged per Superblock

FIGURE 3. Log-Transformed Edge Betweenness in the Bicycle Network

Focusing on superblocks that show low or moderate disruption to the street network (based on edge betweenness change) but high or very high importance in the bicycle network, we identify 17 superblocks for further evaluation of neighborhood suitability. The neighborhood characteristics of the interior streets for our top five superblock candidates are summarized in Figure 4. Nine were selected based on the absence of emergency services (e.g., hospitals and fire stations) and the diversity of local business types. Among them, we ranked the candidates by population size to prioritize areas with greater potential impact, ultimately identifying the top two (Superblocks #30 and #9) as the most feasible superblock locations.

superblock	total_amenities	total_shops	total_offices	total_crafts	total_tourism	total_emergency_services	population	population_density
30	27	35	0	1	0	1*	9919.136762	0.013155
9	27	15	1	0	1	0	9137.043744	0.049173
84	5	3	19	0	2	0	1541.894139	0.046182
136	3	1	1	0	0	0	653.55634	0.043793
116	3	2	6	1	1	0	526.561794	0.017794

FIGURE 4. Top 5 candidates: Neighborhood Characteristics. *NOTE: The correct value is 0. The bbox boundary accidentally includes a hospital on Roosevelt Island.

References

Büth, Carlson M., Anastassia Vybornova, and Michael Szell. 2024. "superblockify: A Python Package for Automated Generation, Visualization, and Analysis of Potential Superblocks in Cities." *Journal of Open Source Software* 9 (100): 6798. `https://doi.org/10.21105/joss.06798`.