IT UNIVERSITY OF COPENHAGEN

BRIDGING SHADE GAPS IN URBAN BICYCLE NETWORKS

A DATA-CENTRIC APPROACH TO TREE PLANTING STRATEGIES

Masters Thesis (KISPECI1SE)

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ABSTRACT

Trees play a significant role in mitigating street-level heat in cities, improving air quality, and providing shade to pedestrians and cyclists. Previous studies have explored the impact of shade coverage on walking routes and thermal comfort, but more detailed and precise models are still needed. Here we explore a data-driven approach to identify shade gaps in bicycle networks to inform policymakers in urban planning about potential tree-planting sites. Our approach is based on creating a model of the existing bicycle network and its surrounding structures. We leverage a combination of open data sources to generate the model, including LIDAR point clouds, satellite imagery, origin-destination pairs, and street network data. Our approach distinguishes between shade provided by vegetation and man-made structures, allowing urban planners to focus on tree-planting priorities. The study is structured as a case study of the city of Copenhagen, Denmark, motivated by the city's current tree-planting strategy. Our findings demonstrate that data-driven analysis can identify opportunities for targeted tree planting within the bicycle network, enhancing shade coverage where it is most needed. However, we also acknowledge that the quality of the data may impact our recommendations. Despite these challenges, our study illustrates the potential of flexible, data-driven urban planning to inform and support tree-planting initiatives for improved urban sustainability and comfort.

CONTENTS

1 INTRODUCTION

As urban planning grows in complexity, it becomes essential to employ more data-oriented methods to efficiently allocate resources and address the diverse challenges faced by modern cities. Trees are a central part of urban environments and provide numerous benefits for its inhabitants, including the reduction of heat islands and improvement of local air quality (Wang and Akbari, 2016; Lai and Kontokosta, 2019). Many of the benefits of urban trees can be attributed to the properties of the shade they provide. Shade at street level can reduce the temperature of surrounding air, thus increasing comfort for pedestrians and users of non-motorized transport like bicycles. Shade also reduces the exposure of skin to UV radiation, which is linked to increased risks of skin-related diseases (Armstrong and Kricker, 2001). Furthermore, over the past years the world has experienced a trend of extreme temperature fluctuations as a direct result of climate change. Exposure to excessive heat and solar radiation is particularly hazardous for individuals with chronic conditions, such as cardiovascular disease, respiratory disease, cerebrovascular disease, and diabetes-related conditions. This heightened exposure can lead to significant deterioration of their health. Even for a healthy individual, excessive sun exposure can cause various health problems, including heat cramps, heat exhaustion, heatstroke, and hyperthermia (Bartholy and Pongrácz, 2018).

With more cities encouraging a shift away from motorized transport, it is important to enable urban planners to make informed decisions about initiatives that benefit the comfort and safety of pedestrians and cyclists. When a city sets out to increase the number of trees, determining the optimal planting locations is a complex and often qualitative process that requires consideration of many factors and stakeholders (Roy et al., 2017). By quantifying some of these factors, planners can make more informed decisions about where to plant trees and how to allocate resources at the city-wide scale.

Project aims

This thesis aims to provide a proof-of-concept for developing a street-tree planting strategy that is based on a data foundation. Our goal is to identify "shade gaps" along bicycle networks that primarily affect residents during daily commuting. We evaluate existing bicycle street networks in terms of shade-coverage and how the current lack of shade can be addressed through urban planning, in particular tree planting.

A central part of this thesis is to work with open data and develop a workflow that is flexible and can be used to evaluate different metrics depending on data availability. As the primary approach, we estimate shade coverage that is cast by existing trees and building structures at street level. This is accomplished by generating a complete 2.5D representation of the urban landscape by utilizing data on building footprints, street vegetation, and elevation data. By employing route simulation based on real-world origin-destination pairs of existing bicycle trips, we identify the most crucial streets of the network in terms of bicycle traffic. Based on all the data acquired, we rank streets in most need of shade and identify locations, that can be best improved by planting more trees.

Two data-centered challenges will be tackled by addressing the following aspects:

1. Accurate calculation of shade coverage at street level. This should be based on the urban landscape but distinguish between shade provided by vegetation and man-made structures such as buildings.

2. Assessing traffic density along the bicycle street network. As the exact data is not available, it has to be interpolated based on a sample of origin-destination pairs of bicycle trips.

By addressing these challenges, we aim to provide a data foundation to assist urban planners in allocating resources for large-scale tree-planting initiatives.

Case Study

Given the varying availability of data for different cities around the world, we have chosen to explore the case of Copenhagen, Denmark. The city is known for its high levels of bicycle usage and centralized urban planning (Nielsen et al., 2013).

The municipality of Copenhagen also aims to plant 38,000 new trees by the end of 2025, with the simple goal "of enhancing the urban nature for its citizens" (Teknik- og Miljøudvalget, 2020). Of the 38,000 trees, 13,500 are to be planted specifically as part of urban development, which includes street trees (Figure 1). The final plan proposal suggests a total of 6,500 trees be planned along streets and parking areas of Copenhagen.

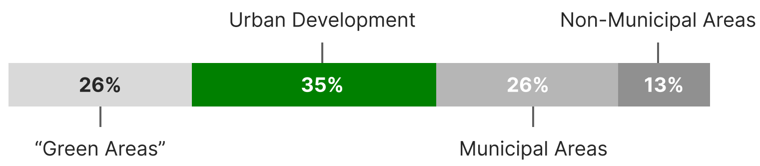


Figure 1: Distribution of new trees in Copenhagen by allocation type

Copenhagen has one of the highest levels of bicycle usage in the world, while also experiencing a changing climate. To that, Denmark has one of the highest rates of skin cancer in the world, which is believed to be partly due to a lack of UV protection during the summer months. A study found that while the majority of Danes use UV protection during outdoor leisure activities, only 19% use it in everyday situations such as commuting (YouGov, 2021).

The shade-casting property of trees could be thus of particular interest to the city of Copenhagen. Consideration of the amount of shade provided by trees by policy-makers and making the urban planning process more data-driven can contribute to more effective decision-making based on available information.

2 | BACKGROUND

Existing studies have demonstrated the significant role that trees play in reducing heat in urban areas (Zhao et al., 2018; Park et al., 2021a). Until recently, only a few studies have focused on directly modeling shade and quantifying its impact on streets. A study by Perez (2020) sought to quantify sidewalk shade coverage using 3D modeling. The study focused on the precision of the modeling, which was achieved through field assessments and manual adjustments to environmental structures. While the study primarily considered demographic data in relation to shade coverage, it also assessed the impact of shade on walking routes. However, the analysis was limited to only 16 routes (totaling 8.5 km) due to the need for manual placement of paths in a GIS software for real-world accuracy. The authors emphasized the number of qualitative factors the 3D modeling depended on, especially the need for manual adjustments to placement, size and the shape of trees. With the need for high precision shade-mapping and the intricacies of 3D modeling, the study relied heavily on ground-truthing the model with Street View imagery, and found fully-automated modeling to be mostly useful for high-level planning analysis.

Jamei and Rajagopalan (2018) used ENVI-met, a state-of-the-art 3D climate modeling tool for environmental analysis and urban planning, to assess the thermal conditions of dense urban centers. They found that shade played the biggest role in improving conditions for pedestrian thermal comfort during hot days. A study by Park et al. (2021b) explored the thermal impact of shading provided by vegetation and building structures using LIDAR, which is a remote sensing method used to examine the surface of Earth. The authors noted the importance of trees and the uncertainty associated with crown size and shade penetrability through leaves. As their analysis did not distinguish between trees and building shade, they identified such differentiation as a potential area for future work.

Overall, these studies highlight the need for more detailed and precise modeling of shade in urban areas, as well as a better understanding of the impact of shade on walking routes and pedestrian thermal comfort.

Tree planting preferences

A study by Lusk et al. (2020) investigated pedestrian and cyclist preferences for tree-planting locations related to sidewalks and bike lanes. Through a visual preference survey, the authors asked over 800 participants along existing bicycle lanes in Boston to choose between five tree-planting scenarios. Among these scenarios, which included *no trees*, there was a stark preference for trees to be planted between the bicycle lane and the street, as opposed to between the bicycle lane and the sidewalk. The majority of participants, including pedestrians, also indicated that tree placement between the bicycle lane and the street was better at reducing the perception of automobile traffic and made them feel cooler. This was backed by a study by Mouratidis (2019), which examined the impact of urban tree canopy cover on perceived safety. Through GIS and survey data, they found a significant association in the perceived safety in both high- and low-density neighborhoods with higher tree canopy cover.

Beauty and Comfort in The Urban Environment

A paper by Quercia et al. (2014) explored the viability of adjusting walking routes based on the perceived *beauty*, *quietness*, and *happiness* of the surrounding area. The study used crowdsourced data, gathered from ratings of urban scenes in London (from Google Street View and Geograph) to quantify the extent to which an area was more or less appealing based on the three dimensions above. They found that the most pleasant routes only resulted in minor increases in walking time while significantly improving the overall perceived experience of the routes. The quality dimensions used in the study were based on another study by the same authors on quantifying a neighborhood's "aesthetic capital" (Quercia et al., 2014). They showcased how the amount of greenery in an area was the most positively correlated cue across all dimensions. Studies like this highlight the relevance of having more quantitative data on the urban environment, as it can be a cheap and effective way to improve the quality of life in cities. They also show the multi-dimensional potential benefits of urban trees.

3 DATA AND METHODS

In this section, we will provide a brief overview of the primary data sources used throughout this thesis. Afterward, there will be detailed subsections for *trees*, *buildings*, *street network*, and *traffic*, covering the processing steps to achieve the final data representation used in the analysis.

3.1 DATA SOURCES

The following data sources were used in this thesis:

SDFI (Danmarks Højdemodel)
We use a Digital Elevation Model (DEM) of Denmark, provided by the Danish Geodata Agency (Styrelsen for Dataforsyning og Effektivisering, 2015). The DEM is based on LIDAR measurements and available as raw point cloud data, as well as a rasterized Digital Terrain Model (DTM) and Digital Surface Model (DSM). The latter two encode the elevation of the terrain (i.e. street-level) and the elevation of the surface including buildings and vegetation, respectively. The resolution of the rasters is 0.5 meters and is provided in bundles of 1x1 km grid cells based on the UTM32-ETRS89 projection.

Municipality of Copenhagen
The Municipality of Copenhagen provides a variety of open data sources, all accessed through the opendata.dk portal. We make use of the *Kommunale Træer* (Københavns Kommune, 2018) which contains records for trees managed by the municipality and *Trafiktal* (Københavns Kommune, 2019) with standardized traffic counts along the road network.

Google
Areal photography of Copenhagen is provided by Google Maps and accessed through QuickMapServices for ad-hoc analysis in QGIS and cached using andolg/satellite-imagery-downloader (2023). The images are downloaded using `zoom = 19` (tile retrieval), resulting in a resolution of 0.16 meters per pixel.

OpenStreetMap
The street network used to represent the bicycle network in Copenhagen is provided by OpenStreetMap (OSM). The network is accessed through the Python module `OSMnx` (Boeing, 2017) which provides both a structural graph representation of the network, as well as spatial representation of the street segments. To that, `OSMnx` also allows for the retrieval of additional tagged entities from OSM, such as street properties and building footprints.

Tier Mobility
Origin-destination (O-D) pairs of rentable e-bikes from the vendor *Tier Mobility* are extracted through scraping. This is done using the Python-based tool *TierScooter-Analysis* by Marco H. (2021), which builds an SQLite database recording unique `bike-id`, `timestamp`, `location` etc. Records are collected in 20-minute intervals over a 2-month period (from February 20th to April 22nd, 2023) for the Copenhagen operating area.

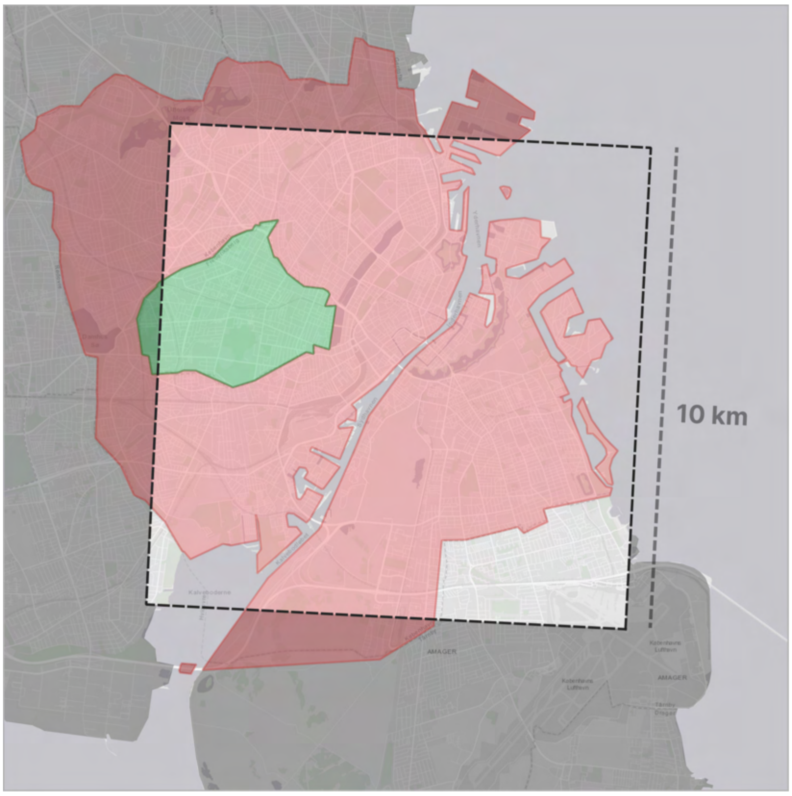


Figure 2: Study area depicted by 10x10 km cell (from `UTM32-EUREF89` grid)
● Municipality of Copenhagen
● Frederiksberg Municipality

3.2 STUDY AREA

Copenhagen is Denmark's capital and most populous city, with a population of over 600,000 people. The city is known for its extensive network of protected bike lanes, pedestrian-friendly streets and a number of green spaces and parks. For practical reasons, we limit our study to a single 10x10 km grid cell in the UTM32 coordinate system (Figure 2). This area covers most of the Municipality of Copenhagen, the enclaved Frederiksberg municipality, and a part of Tårnby (north of Copenhagen Airport).

Such an area allows both central planning and dividing it to focus on smaller areas and neighborhoods. It is also the format used by the Danish Geodata Agency and Statistics Denmark, which makes future use of the results convenient in the context of urban planning in Denmark.

3.3 TREE EXTRACTION

Limited data is available on urban vegetation in Denmark and less so for information on tree locations and canopy sizes. The Municipality of Copenhagen does offer the dataset *"kommunale træer"* (Københavns Kommune, 2018). It is a register of 62,000 trees that are managed by the municipality. While large, it is far from complete and a lot of street trees are not part of the dataset – likely because of ownership by private or other governmental entities (exemplified in Figure 3). For the vast majority of entries, there is also no further information on tree species, age or size, adding to the difficulty of generating an accurate shade map from vegetation.

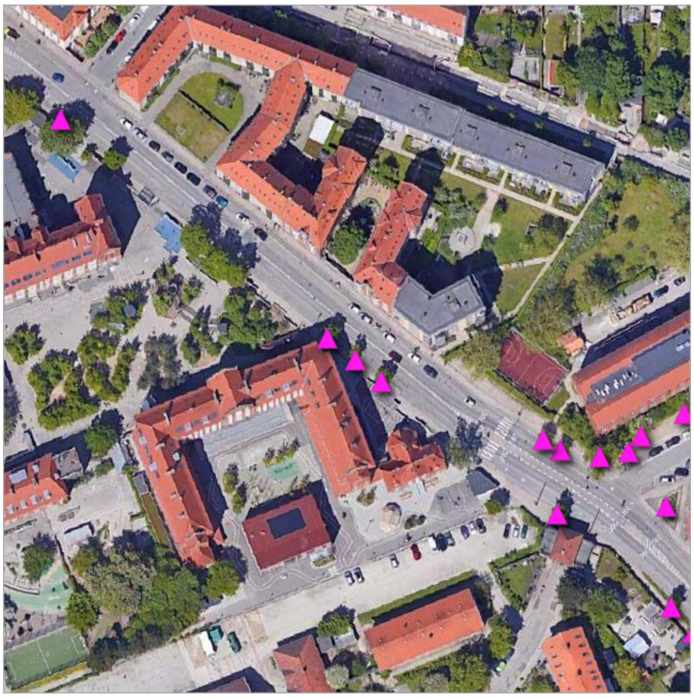


Figure 3: Part of Amagerbro (Copenhagen) with trees from the *"kommunale træer"* dataset marked with ▲. Many visible trees are not in the register. Basemap: ©2023 Google

Instead, to accurately detect and measure the dimensions of trees and their canopies in Copenhagen, we will extract this information using a mix of publicly available areal data including satellite imagery and elevation models. From these, we can extract a canopy height model (CHM) which encodes the above-ground height of any structure (including vegetation):

$$\mathrm{CHM} = \mathrm{DSM} - \mathrm{DTM}$$

Tree detection

Most tree segmentation algorithms based on LIDAR require the tree positions to be known. The first step thus involves detecting individual trees by recording the position of each tree top. Existing approaches for individual tree detection often use a local-maxima algorithm on the canopy height model (CHM) (Wu et al., 2016; Liu et al., 2015). Traditionally, this has been effective within forestry applications where the majority of height peaks belong to trees. In urban settings, however, the CHM is often filled with many height peaks that are not trees, such as buildings or light poles.

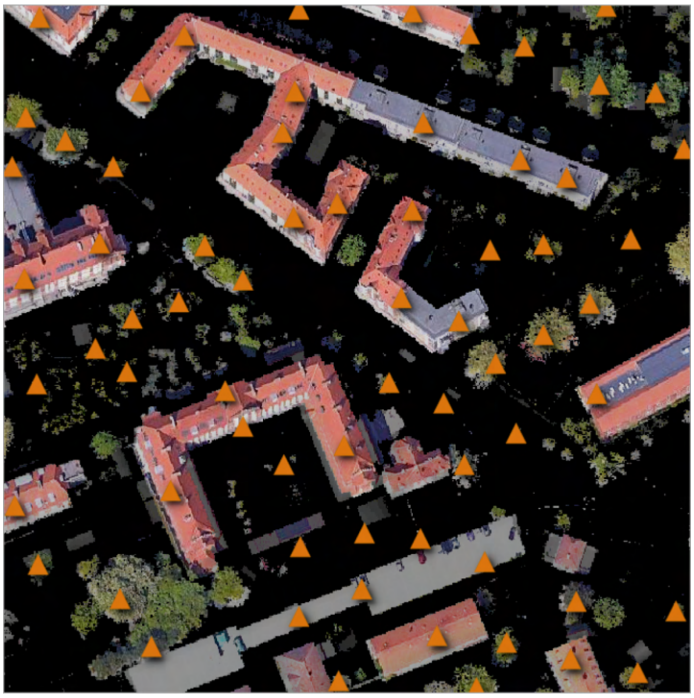


Figure 4: Algorithmically identified tree tops marked by ▲ using local-maxima algorithm ($ws = 20$) on raw CHM.

Simply applying the local-maxima algorithm on the raw CHM results in many false tree-top identifications (see Figure 4). To overcome this, we introduce a masking step to discard all non-greenery from the CHM. This is done by using a version of the `facebook/maskformer-swin-base-ade` segmentation model that is specifically fine-tuned for urban greenery detection (Hersan, 2021). The model uses areal imagery as its input and generates a raster mask covering areas with trees. A range of factors are important to consider for it to be useful for the masking step, which include:

1. **Up-to-date** The imagery should be as recent as possible to accurately represent the current tree distribution and landscape. In our case, the mask only serves as a pre-processing step and thus recency is not a priority, as the CHM we are masking is captured in 2018.

2. **Quality** Images should have vivid enough colors, sufficient clarity, and resolution.

3. **Season** The imagery should be captured during summer or late spring when trees have full foliage.

4. **Perspective** The angle of the imagery should be as close to nadir (perpendicular to the surface) as possible to minimize skew and shifts relative to the CHM.

5. **Shadows** Most areal imagery is captured during clear days, which can result in dark shadows that obscure parts of the greenery. Thus, it is important to use images that are captured as close to noon as possible to minimize shadows.

Finding a source that satisfies all these requirements is not easy. We experimented with 5 different providers and ended up using Google Maps which was the most consistent (with a large margin) with respect to the above factors. A comparison of the different providers is included in the appendix. The images are extracted

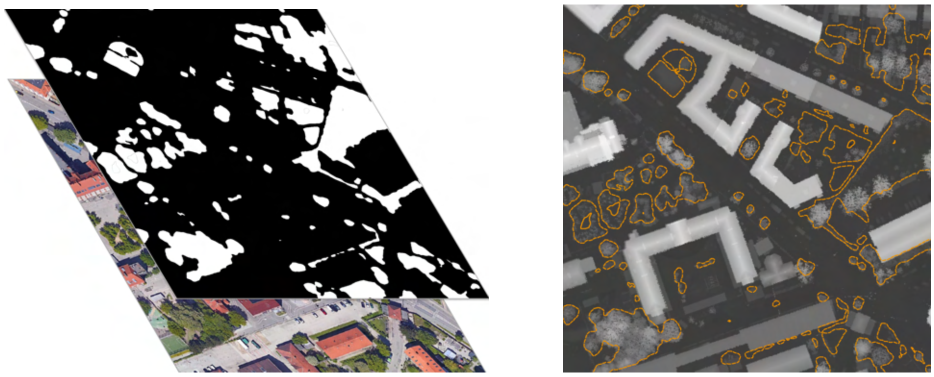


Figure 5: Extracted vegetation mask from areal imagery (left) and vectorized vegetation mask reprojected onto CHM (right)

as tiles matching the CHM bounds and resolution. Because Google uses the Web Mercator projection for its imagery, we overscan the tiles by 10% to account for the shift after reprojecting to ETRS89 used by the CHM.

The raster mask is then vectorized, after which a 1.5-meter buffer is applied to account for possible misalignments between the CHM and the imagery. The resulting mask is then reprojected onto the CHM and used to clip the raster such that it mostly contains areas with trees (see Figure 5). The last processing of the CHM involves clipping all values below 1.5 (meters) to remove any ground noise as well as smoothing the raster using a Gaussian filter (radius 2). At last, the local-maxima algorithm is applied to the processed CHM to extract the tree tops.

```
# Tree detection
tops <- locate_trees(
  chm,
  lmf(7)
)

# Tree segmentation
algo <- dalponte2016(
  chm,
  tops,
  th_tree = 1.5,
  th_seed = 0.28,
  th_cr = 0.50
)
```

Code 3.1: Parameters for lidR tree detection and segmentation algorithms

Canopy segmentation

After having extracted the locations of the tree tops, we can now use the LIDAR point cloud to extract information about the tree canopies. We use the `lidR` R-package which implements a range of published algorithms for tree segmentation using point clouds. We use `dalponte2016` (Dalponte and Coomes, 2016) which is a seed-based algorithm that uses the tree tops as starting points (seeds) to grow the canopy, initially based on the raster CHM. When the algorithm reaches its growing threshold, the convex hull is used to extract the canopy area from the point cloud (Figure 6). The parameters used for the tree detection and segmentation algorithms are listed in Code 3.1.

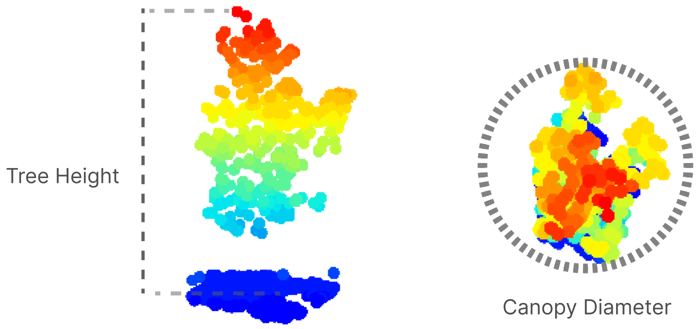


Figure 6: Point cloud plot of a single tree. Side profile view, illustrating the vertical structure and height (left), and top-down view on displaying the crown shape (right)

Figure 7: Segmented tree canopies marked in dashed circles ●

To simplify the representation of the canopy, we approximate it using a series of circular slices, each defined by its height above the ground and the diameter of the smallest circle that fully encloses it. Slices are taken at a fixed height interval of 0.5 meters.

Extracting all trees in our study area using the above approach results in a total of 219,000 trees (final representation illustrated in Figure 7). Of these, about half (127,000) are located within 10 meters of a street in the bicycle network. Comparing the *kommunale træer* dataset to the extracted trees, we get a recall of 0.41. While this is not particularly high, a significant amount of trees in the *kommunale træer* dataset are found in dense clusters in parks and along paths, often obscured by other larger trees. To that, many trees are newly planted or have crowns too small to be detected in the CHM. We, therefore, deem the missing trees to have only a minor impact on the total shade contribution. From a sample of 5000 trees in our dataset, only 9.2% were within a 2 meter radius of a tree in *kommunale træer*.

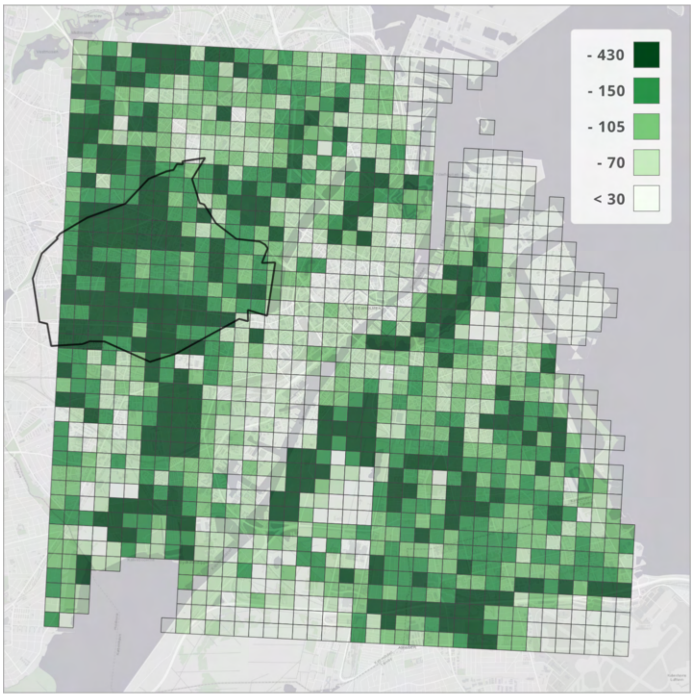


Figure 8: Counts of extracted trees in Copenhagen aggregated over 250x250 meter cells. Frederiksberg outlined in black.

From the tree density plot (Figure 8), it is clear that the extracted trees are far from evenly distributed across the city. Most notably, the densely populated Frederiksberg Municipality has a significantly higher density of trees compared to the equally population-dense neighborhoods surrounding it.

3.4 BUILDING GEOMETRIES

We generate 2.5D models of buildings within Copenhagen using the building footprint data from OpenStreetMap (OSM). While this data provides accurate outlines of each building, it lacks information regarding their height. To address this lack, we uniformly sample 3 points/m^2 over the area of each building's footprint from the corresponding CHM raster, giving us a set of heights that reflect the height of the building at various locations.

Next, we create the 2.5D models by extruding the 2D building footprints to their respective heights. It is important to note that these models do not consider potential differences in height across the roof surfaces, such as sloping roofs. To account for any variations in height, we use the median sample height as the definitive measurement for the building, ensuring that the model's height is as representative as possible of the actual building.

Occasionally, OSM data may contain building objects with multiple geometries for different building portions. However, these instances are relatively rare, comprising less than 5% of all geometries in our dataset, and generally do not have any structural height differences.

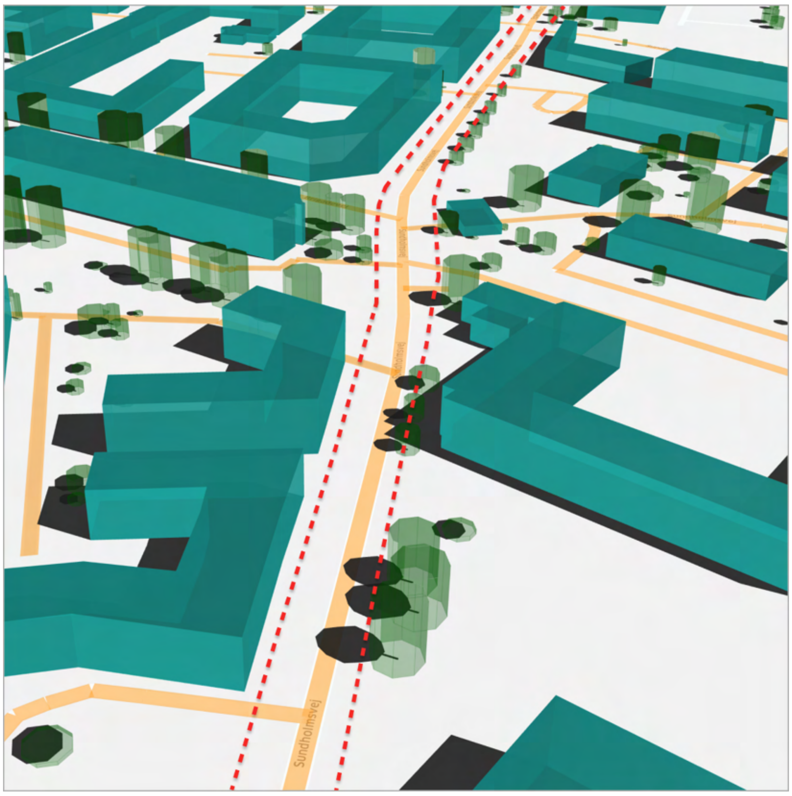


Figure 9: 3D rendering of the modeled buildings representations (footprint extrusions), tree placements, and street network along *Amagerfælledvej*.
OSM bicycle network (centerline representation)
True position of bicycle paths along *Amagerfælledvej*

3.5 TRAFFIC DENSITY

To assess the daily usage of the street network, we have to access real-world traffic data specifically for cyclists. Such data is hard to come by and we therefore resort to collecting real-time positions of rentable e-bikes from the vendor *Tier*. They operate approximately 1,500 e-bikes throughout Copenhagen. Their API endpoint provides information on the current location of all available e-bikes that are not currently in use. Along with location information, the endpoint also provides a unique identifier for each e-bike as well as its battery level. Since this endpoint cannot track e-bikes while they are mid-journey, we extrapolate the origin-destination pair of journeys for each e-bike. Additionally, we also access information on operational boundaries, which may introduce further restrictions on e-bike usage such as forbidden parking areas.

To extract the origin and destination points from the logged e-bike records, we discard records that meet any of the following criteria:

1. Location changes < 500 meters
   (For instance, noisy GPS data or insignificant relocation)

2. Battery level increase after a location change
   (This indicates a relocation by the vendor)

3. An e-bike has been offline for more than 1 hour

After cleaning, we are left with a total of $31,500$ unique origin-destination pairs.

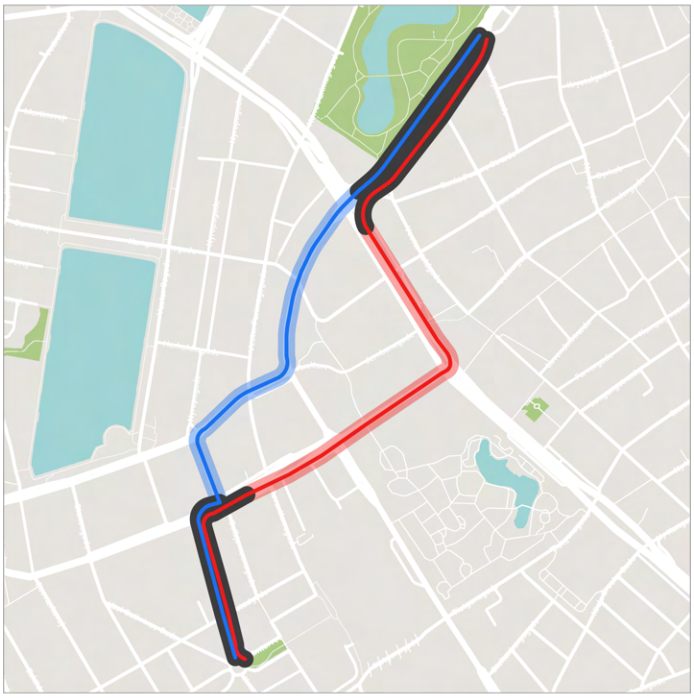


Figure 10: Illustration of agreement between two routes (Google Maps ● and OSM ●). A 2-meter buffer is drawn around each path. Any sub-segments of a path that intersect with the other path's buffer are considered to be *in agreement*.

3.5.1 Route Interpolation

Since the exact routes of e-bike journeys remain unknown, we attempt to estimate the most likely route by utilizing a routing engine. It is crucial to mention that if the routing engine solely incorporates network distance as its minimization objective, interpolated routes may not accurately represent real-world traffic patterns. Thus, we have run a small meta-experiment comparing routes generated by two routing engines: a naive shortest-path calculation on the combined road and bicycle network from OpenStreetMap (OSM), and another derived from the proprietary Google Maps *Directions* API. Google Maps is presumed to consider additional information when routing (such as traffic, elevation, and minimizing turns), positioning it as the benchmark for bicycle routing in Copenhagen. Ideally, we would prefer using OSM due to its integration with our data and licensing, but a low agreement between the two interpolated routes would indicate that the additional information used by Google Maps significantly affects and better reflects the actual traffic patterns.

As the two sources' base street networks are not identical and lack a 1:1 alignment, we define agreement as the percentage of a path that intersects with a 2-meter buffer of the other path (illustrated in Figure 10). The comparison shows that only 38% of OSM street segments align with the Google Maps routes, and the average route length shows a negligible deviation between the two routes.

We thus proceed with processing all 31,500 O-D pairs using the Directions API. The interpolated route paths are then stacked and aggregated using a line density algorithm, resulting in a density raster with a linear relationship to the number of paths passing through each cell. We use a search radius and pixel size of 10 meters to account for misalignment between the interpolated routes and the underlying street network from OSM. The line density raster is then sampled around each street segment using a 1-meter window and the resulting mean value is used in the

Figure 11: Line density raster of interpolated routes from e-bike O-D points

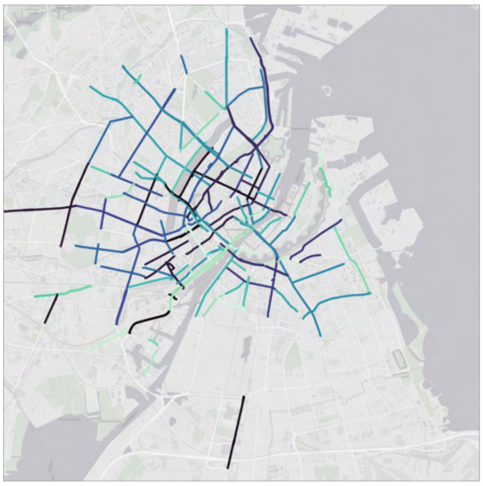


Figure 12: Discrete groups of street segments after vectorization and trimming. Filtration is based on the upper quartile of traffic density

vectorized representation. The network is then trimmed based on a traffic threshold and direction, such that segments mostly belong to the same continuous stretch of street. This way we can reference discrete parts of the street network during the analysis step (illustrated in Figure 12).

As can be seen in Figure 11, the resulting density raster is highly concentrated around the city center, with a few exceptions. This can be attributed both to e-bikes being more prominent in the city center (due to economic incentives for the vendor) and the generally higher volume of bicycle traffic that passes through the area. To mitigate this bias, we make use of the *Trafiktal* dataset (Københavns Kommune, 2019) which provides standardized traffic counts across the city, including the Frederiksberg municipality. There s a total of 1108 counts in our study area of which 633 contain bicycle counts. All counts are performed on weekdays during a 12-hour window (7:00 AM to 7:00 PM). We thus join the closest street segment to each counting location and extract a scaling factor for each point based on the divergence from the mean ratio between interpolated route density and the actual traffic counts, $\bar{R}$ (see equation 1).

$$\bar{R} = \sum_{i=0}^{n} \frac{\log(\text{interpolated traffic density}_i)}{\log(\text{true traffic count}_i)} \cdot \frac{1}{n} \tag{1}$$

Figure 13: Mean traffic ratio from which divergence is calculated. With $\bar{R}$ being the mean log-ratio and n the total number of traffic count locations.

The divergence from $\bar{R}$ ranges between -1.2 and 0.9, for which we min-max normalize to the range of $[0, 2]$ and use this as the scaling factor. As we are working with discrete counting locations, we use a spatial interpolation method to estimate the scaling factor across different areas, specifically *Inverse Distance Weighting*, which provides a smooth interpolation based on the distance to the nearest values.

The interpolated scaling factor across Copenhagen is illustrated in Figure 14. This clearly shows that the interpolated routes are biased towards the city center (especially east of the Copenhagen Lakes), and that the scaling factor is generally higher in the outskirts of the city. It is notable that in areas around transit hubs, the scaling factor is below 1.0, even outside the city center. This shows how rental e-bikes are to a higher degree used for first- and last-mile trips to and from transit hubs, again

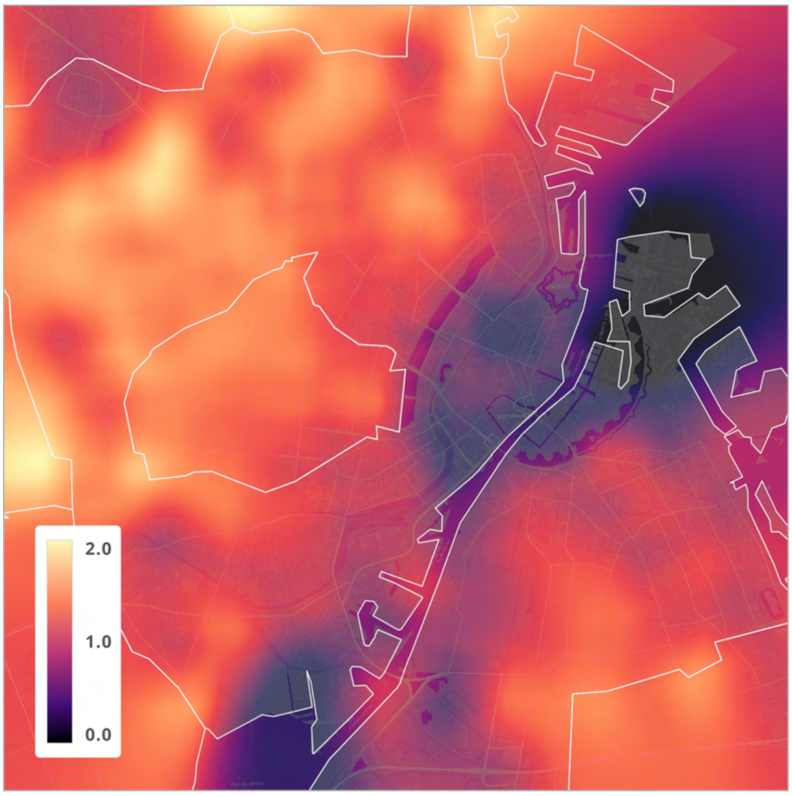


Figure 14: IDW interpolated scaling factor based on the divergence of real-world traffic counts from interpolated route density. Smoothed using mean-filter with radius = 10.

highlighting the difference between the traffic patterns of rentable e-bikes and regular bicyclists. Lastly, interpolated scaling factor raster is sampled around each street segment and used to scale the traffic density.

3.5.2 Centerline shifting

As illustrated in Figure 9, the OSM bicycle network is not always aligned with actual bicycle paths and is mostly based on a single centerline through the street. This can be a problem when the spatial accuracy of the bicycle network is important as bicycle lanes are mostly found on the side of the street, in between sidewalks and car lanes.

To address this, we parallel-shift the centerline of each street segment by a fixed distance. To start, the centerline is split into fixed-length sub-segments of 3 meters. The sub-segments are then buffered to the desired street width (W), while another buffer is created with a width of $W - 1$ meters. The difference between the two buffers is then used as the new spatial representation of the bicycle network. The paths consist of connected 1×3 meter cells, which are used as the base unit for the analysis step. This shifting process is illustrated in Figure 15 with the full workflow available in the appendix.

With street width varying across the city, we use a conservative street width of 4 meters. Street width could also be interpolated on a per-street basis, by measuring the mean distance to the known structures surrounding the street, such as trees and buildings. That is however outside the level of detail of this project, and we thus leave it as future work. Nevertheless, this could improve the adaptability to other cities and lead to even more accurate shade estimates.

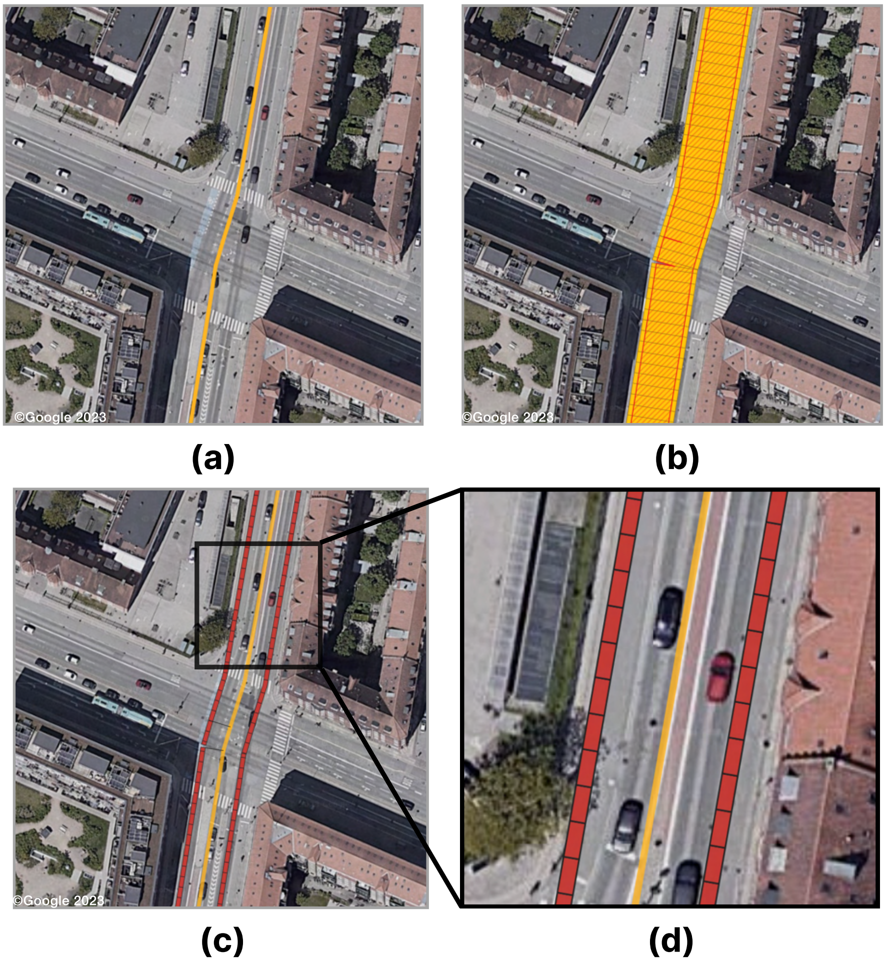


Figure 15: Steps of the centerline shifting process. The original centerline is shown in **(a)**, which is split, buffered **(b)** and intersected **(c)**, resulting in two parallel streets made up of unit-segments **(d)**.

4 TREE SHADOWS AND PLANTING

The process of designing a tree planting plan is a multifaceted problem that can be approached in multiple ways - starting with the choice of the level of precision or the decision of central vs. local planning - and all those variables can greatly influence the final outcome of the plan. This chapter aims to explain each of these decisions.

The foremost of the three main choices to be made concerns the modeling of tree shapes and the precision with which it should be accomplished. This consideration is a trade-off between the quality of the acquired data and the complexity of the calculations and model. The ideal compromise produces data that is sufficiently representative of the real world while being of adequate precision and complexity to permit convenient reprocessing and relatively high speed of calculations.

The second key issue relates to the flexibility of the tree planting plan. While it is conceivable to develop a single comprehensive plan for the entire city, it may be sensible to partition the vast area into smaller segments or tiles. This approach allows for greater autonomy in developing various neighborhoods within the city while also reducing the possibility of bias due to the overrepresentation of the central region of the city in the traffic density data. However, different types of segments can generate significantly different solutions, and the choice of particular neighborhoods should try to reflect the actual separation of the city under the aspect of interest.

The final matter for consideration pertains to the algorithm for tree planting itself and the assessment of the delivered solution's quality. No single universally applicable metric exists for this purpose, and there is no ideal benchmark tree distribution plan against which the results can be compared. Consequently, it is essential to think about the objectives of the plan and determine the most precise methods for evaluating the extent to which they have been achieved.

All code and resources used in this project are available at:
github.com/edibegovic/shadow-routes

4.1 SHADOW GENERATION

As initially described in the *Tree detection* section on page 8, each tree in our dataset is described by the total height and canopy diameter. All tree crowns are imagined as an ellipsoid, with its widest point having a given diameter. Such an assumption allows projecting a shadow very quickly, by calculating separate shadows for several horizontal coronal planes and combining them by a simple convex hull, which is illustrated in Figure 16.

Due to the difficulty of extracting precise information, the lower edge of the crown is assumed to be at a fixed point mid-height. Since we do not have enough data on light transmission through the canopy and it is not necessary for our analysis, we also assume that the tree crown is impermeable.

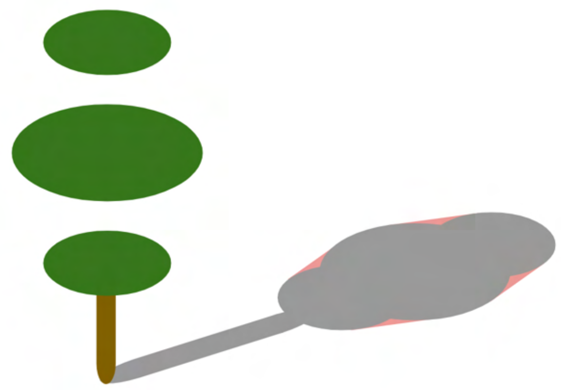


Figure 16: Visualization of three horizontal planes crossing the crown of the tree and the shadow created by them. Red areas are filled using convex hull.

4.2 ANALYSIS AREA

Bicycle traffic tends to be higher around the city center, and it is easy to over-focus on improving these central locations while neglecting more remote streets. The ideal situation involves a network of main, shaded arteries extending throughout the city, allowing people to travel even between remote neighborhoods, and connecting paths that can get more sunlight since most parts of the route do not go through them. Therefore, we decided to not only create one central plan for the entire study area but also locate the most key routes for many smaller segments, and compare obtained results. A solution using some method of division has the added advantage of being more adjustable to external factors, such as financial constraints or the desire to green specific urban areas for additional reasons, allowing the changes to be implemented in different neighborhoods independently.

As the base grid, we use the Danish quadrant system (Det Danske Kvadratnet), which is a standardized geographical grid used in Danish surveying and statistics. The grid cells are 1x1 km and are numbered, using the UTM coordinate system (Zone 32). This approach has some advantages, among which are the equal size of the segments and the fact that they are fixed and unchanging over time. However, the division created is somewhat artificial, not taking into account the structure of the city, and far from how the city's various internal boundaries are actually perceived. Therefore, we decided to expand our analysis to include alternative ways to segment the city and test their impact on the final results.

One of the other possibilities is to use the constituencies currently used in the Greater Copenhagen area, which provide us with segments of comparable population density, which largely coincides with commonly recognized neighborhood areas in Copenhagen. However, one must bear in mind that the proposed areas are significantly larger than the base 1x1 km grid.

Another alternative could be parish boundaries, which also approximate areas of similarly populated areas. The advantage of this method is a more reasonable size of one segment, however, such a division may not be the most relevant due to the historical method of determining its boundaries. All the aforementioned divisions are illustrated in Figure 17.

Figure 17: Alternative ways to divide the case study area - using Danish quadrant system (left), constituencies (middle), and parishes (right) borders.

4.3 TREE PLANTING PLAN

Street trees are nearly always planted together in multiples. Trees in groups contribute to creating variation in the streetscape, giving the perception of more nature, more robust plantings, and help to minimize the average installation cost per tree (10-30%). In 2020, the mean distance between trees on municipal streets in Copenhagen was 25 meters (Teknik- og Miljøudvalget, 2020). On the other hand, shading of side streets with little traffic, even if it is relatively inexpensive or can achieve almost 100 percent shading, should not be a priority from the point of view of our analysis, where one of the important aspects is precisely the usability of the analyzed routes. With the above in mind, different approaches to tree planting plans can be considered. One can involve prioritizing filling shade gaps on roads with existing long spars of trees, when the opposite approach looks at traffic on the street first and allows for extreme solutions where multiple trees need to be planted next to each other because the street was initially (almost) empty.

Bearing in mind all possible scenarios, we decided to parameterize the code with a few different variables, which are:

- *Budget*: As mentioned in section *Centerline shifting* on page 16, part of data preprocessing is dividing streets into small segments of about 3 meters each. Then the budget is considered as the number of segments that can be marked as "possible to plant trees".
- *Alpha coefficient*: With two opposite approaches described, one prioritizing the development of high-traffic roads, and the other focusing on the maximal shadow possible, we created an alpha coefficient that defines the proportion of influence of the two approaches, where a value equal to 1.0 gives full weight to the impact of traffic, while 0.0 ignores traffic altogether.
- *Minimum no. segments in a row*: Taking into account that it is the travel of longer stretches of road in full sunlight that is most inconvenient, as well as the fact that the cost of planting trees in a row is significantly lower than planting individual trees, we take into account the possibility of defining a minimum number of segments in a row. In such a situation, if the number of consecutive unshaded segments is less than the defined parameter, such a route segment is not considered as a potential tree planting site.
- *Minimum shade*: To enable the shade maximization variant, we introduced the minimum shade parameter, which defines how much the street must be minimally shaded after planting all possible trees (defined in percent). Streets that are unable to exceed this threshold due to the minimum number of segments parameter are excluded from further analysis.

- *Minimum traffic*: In order to focus only on routes of high enough importance in travel, we created a parameter minimum traffic that determines how much traffic a street must have for it to participate in the analysis. This parameter takes values from 0 to 1 and is interpreted as a quantile value.

Using the above variables, the process of selecting streets for tree planting is as follows. As the first step, traffic is normalized for the area of the current analysis, and the network is filtered to meet the conditions for minimum significance. Then, taking into account the minimum no. of segments in the row, we calculate the number of segments of each road that can be marked as "plantable." Taking this into account, we calculate how shaded the road will be if 100% of the plan is carried out, and if the value obtained is less than the minimum shade parameter, the road is excluded from further analysis. Then the score is calculated as defined below:

$$score = \alpha \cdot traffic + (1 - \alpha) \cdot shade$$

All the streets are then ranked by this score and selected in the given order unless the budget is exhausted. When considering multiple neighborhoods, the budget is divided proportionally to the area of the neighborhood.

5 | ANALYSIS

In this section, we present the findings of our analysis. We start by introducing the study area and its characteristics, and then proceed to a presentation of different recommendations for tree-planting strategy. We qualitatively evaluate the results by inspecting street-level images of the sections.

Shade analysis

Throughout the analysis, we use the day of the summer solstice in Copenhagen as the basis for shade projections. This period is also characterized by minimal cloud cover and the highest UV index of the year. Sun position can be described by two angles: the azimuth and the altitude. The azimuth is the angle between the sun's position and true north (measured clockwise), while altitude is the angle between the sun's position and the horizon. We project the sun's position for the summer solstice at three different times of the day: 09:00, 13:00, and 17:00. At 13:00, the sun is at its highest altitude, also resulting in the highest UV-levels and the shortest shadows. At 09:00 and 17:00, the sun is at a lower altitude, but at these times the bicycle traffic, especially from commuters, is higher.

Green paths

The Municipality of Copenhagen has since 2000 prioritized the development of so-called "green cycle paths" in the city. The routes are designed to be useful both for commuters and recreational cyclists, providing a separate cycling environment surrounded by greenery. As of 2015, the network stretches 58 km, with another 51 km planned for the future (Københavns Kommune, 2016).

Figure 18: The Copenhagen *Green Cyclepaths* network
Green paths
Sections of green paths with *high* traffic

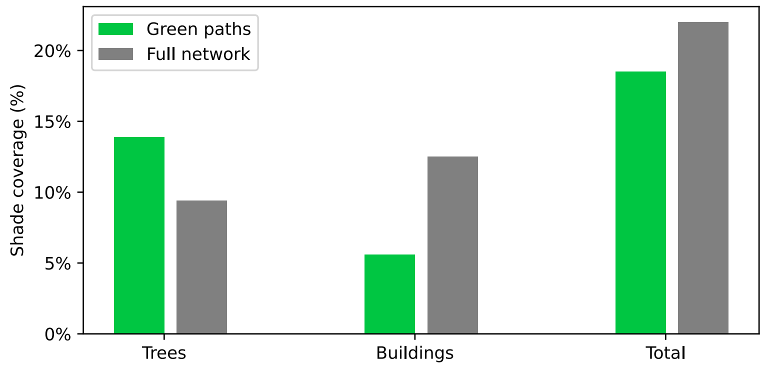


Figure 19: Comparison of the mean shade coverage (full day) of green paths and full street network

The current iteration of the network (as of 2023) is shown in Figure 18. Despite the paths being part of a larger bicycle-friendly network (often referred to as *bicycle super-highways* in many planning schemes), the majority of the bicycle traffic in Copenhagen only passes through a small fraction of the green paths. We set out to analyze the shade coverage of the network to establish a baseline for *high* shade coverage.

To establish a baseline for the entire street network, we calculate the full-day mean shade coverage from the three time periods (09:00, 13:00, and 17:00). The same is done to the combined green path network. A comparison of the two based on the proportions of shade provided by trees and buildings is shown in Figure 19. Green paths have close to 50% more shade provided by trees than the full street network, while a much smaller proportion comes from buildings (−56%). Despite the higher concentration of trees, the green paths have lower overall shade coverage and are only marginally higher than the full network during the Zennith period (13:00).

Route	Tree shade	Length (km)
Den Grønne Sti	35.2%	3.73
Danshøjruten	28.5%	0.19
Vigerslevruten	28.4%	0.40
Christianshavnruten	24.6%	0.47
Lufthavnsruten	22.1%	0.79
Hvidovreruten	21.2%	1.26
Nørrebroruten	19.5%	1.68
Svanemølleruten	14.8%	0.70
Amagerruten	13.6%	0.20
Valbyruten	9.2%	0.47
Hareskovruten	9.1%	0.10
Refshaleruten	8.5%	0.14
Frederiksbergruten	7.7%	3.23
Carlsbergruten	7.6%	0.62
Havneringen N og Langelinieruten	7.2%	0.24
Kastrupfortruten	6.9%	0.37
Ørestadsruten	5.3%	0.30
Havneringen	4.9%	0.21
Kalvebodruten	4.3%	2.59
Havnringen N 2.2	1.7%	2.90
Havneringen N 2.1	1.4%	0.46

Table 1: All 21 green paths ordered by their mean full-day shade coverage

The green paths network is divided into 21 distinct routes, which are all named and make up a continuous stretch (listed in Table 1). From the table, it is clear that there is a large variation in the shade coverage of the different routes. Most notably, *Den Grønne Sti* has a shade coverage of 35.2%, despite being one of the longest routes (3.7 km). We can thus conclude that the green paths network is not uniform in terms of shade coverage, is designed with more factors in mind, such as providing safe, detached and scenic routes for cyclists.

Experiments

We decided to conduct tree planting experiments in three possible parameter configurations. The first case is the base configuration, which is intended to simulate a general approach to urban planning that does not focus on any particular aspect. In the second case, traffic prioritization, the focus is on the importance of streets in terms of travel, and more weight is given here to traffic on individual roads. The last case maximizes total shade and favors roads that can be almost completely covered. Detailed parameter values for all experiments can be found in the appendix.

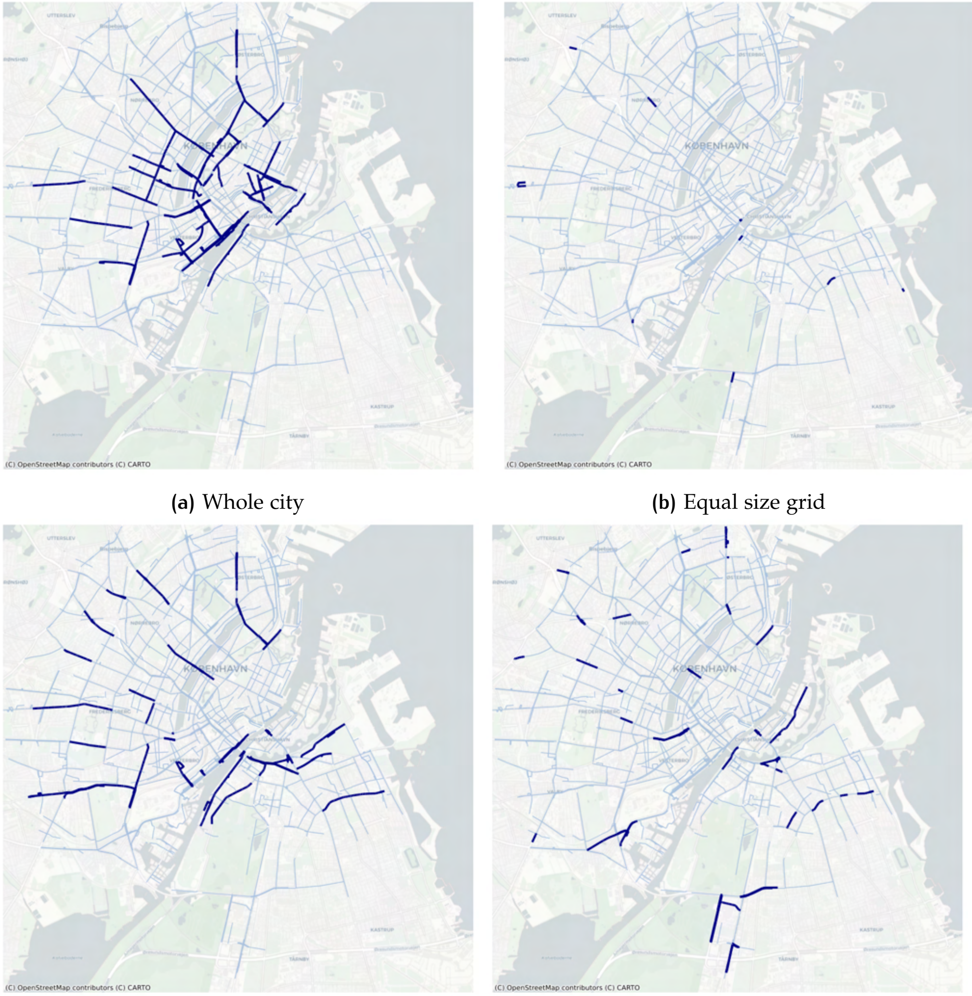
5.1 BASE APPROACH

As the first case is intended as a starting point for further analysis, it assumes a uniform effect of shadow and traffic on street selection. This approach helps to observe the differences between the different ways of dividing the city for the results obtained. In Figure 20 we report the results of executing the algorithm using particular analysis areas, with budget split proportionally to the area of the segment. Immediately one can see that the recommendations presented differ significantly from each other. For the results on the city's entire bicycle network, as expected, the greater concentration of selected paths is in the city center. Constituencies and parishes produce much more scattered results, with the former at the same time maintaining more continuity between parts of the road. In contrast, the results obtained by the grids are not satisfactory. A very small number of sections were selected and they are scattered randomly throughout the grid.

Such outcomes follow intuition. With central planning, it is easier to create a coherent plan at the expense of neglecting remote neighborhoods. Considering smaller areas separately provides an opportunity to look at their needs individually, but it is difficult to have the larger perspective needed to ensure, for example, the continuity of suggested routes. On the other hand, a too-small distribution grid will result in too much fragmentation of the available budget, blocking the selection of any routes. This is clearly visible in Table 2 - while constituencies and parishes still provide some input and may be used as supplementary for the whole city's urban planning, the grid analysis area is too fragmented to bring value, and for this reason, not considered in further experiments.

Approach	Number of streets selected	Total length of streets selected (km)	Budget used
Whole city	44	90	99%
Grid	11	3	3%
Constituencies	46	64	77%
Parishes	36	38	39%

Table 2: Overview of different areas of analysis.



(a) Whole city

(b) Equal size grid

(c) Constituencies

(d) Parishes

Figure 20: Results for the base configuration.

5.2 TRAFFIC PRIORITIZATION VS. MAXIMIZING SHADOW

One of the interesting areas in our analysis was whether a focus on different aspects of urban planning would produce significantly different results. In our experiments, we decided to look at this by testing two options - one focusing on the relevance of roads in terms of traffic, the other rewarding the possibility of creating routes that are almost fully shaded. The results of such a comparison are shown in Figure 21 - differences are clearly visible, but the general shape of the streets proposed remains the same. Quantifying this similarity by calculating the intersection of two sets of streets over the union of these sets can be seen in Table 3 - one can see that for all three areas of analysis obtained values are similar. Based on the relatively small number of streets shared, it may be concluded that the two approaches differ significantly enough to derive a value from using them separately.

	Whole city	Constituencies	Parishes
Common streets	24%	27%	21%

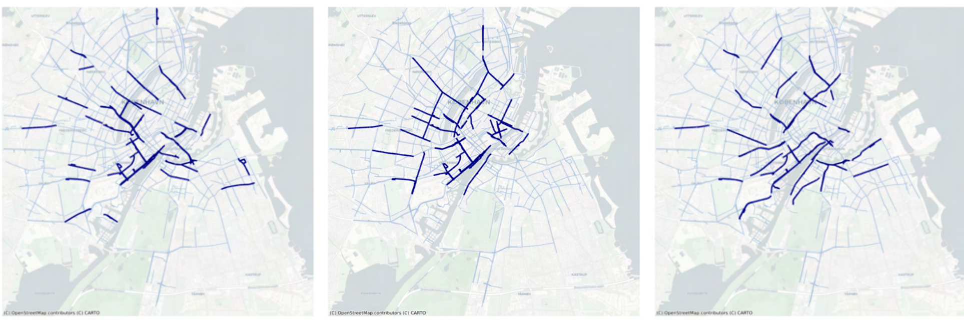
Table 3: The percent of common streets for each variant.

Figure 21: Comparison of traffic prioritization approach (top row) vs maximizing shadow (bottom row)

5.3 TIME OF THE DAY

Another aspect we wanted to consider in our analysis was the differences in the plans produced, depending on the time of day for which the shadow data was acquired. As mentioned before, three different times of the day were collected: 09:00, 13:00, and 17:00. While all previous analyses were based on data for the sun at the zenith, here we want to determine whether, using the other hours, the resulting recommendations will differ significantly.

Sample recommendations for the whole city are shown in Figure 22 and at a glance, they may look similar to each other. However, quantifying the number of common roads, calculated as the intersection of three street sets over the union of them, shows that only around 10-15% of them are actually in all the sets (Table 4). This points to a problem regarding the recommendation of planting trees due to the amount of shade - a decision should be made having a particular time of the day in mind. In part, this problem can be dealt with, for example, by calculating the score for different times of the day to draw an average from it, or by trying to extract the subset of streets found in each independent recommendation.



(a) 9:00 **(b)** 13:00 **(c)** 17:00

Figure 22: Comparison of results obtained for different times of the day.

	Whole city	Constituencies	Parishes
Common streets	10%	17%	11%

Table 4: The percent of common streets for each variant.

5.4 IMPROVEMENT COMPARISON

A valuable perspective may be to look at the numerical outcome of each variation of the algorithm. A general overview of the maximum amount of shade for each time of the day can be seen in Table 5. The differences obtained may look insignificant, however, one should have in mind that from the entire network perspective, only a small fraction of the streets are selected for tree planting. Table 6 focuses on a smaller part of the network and shows the amount of the final shadow only for the subset of improved streets. It reveals that the average shading values on these roads reach values over twice as high as the mean shade within the *Green routes*. Such information meets our expectations, because the goal of the algorithm is not to shade every street in the city - on the contrary, to select a sufficiently large subset of streets that will create a thermal comfortable travel alternative.

		9:00	**13:00**	**17:00**
Without tree planting recommendations		28.06%	14.19%	24.62%
Base configuration	Whole city	32.37%	18.69%	29.20%
	Constituencies	30.00%	17.14%	27.09%
	Parishes	29.46%	15.30%	25.98%
High traffic	Whole city	31.68%	18.61%	28.25%
	Constituencies	29.72%	16.85%	26.86%
	Parishes	29.07%	15.08%	25.48%
Maximum shade	Whole city	32.55%	19.00%	28.99%
	Constituencies	30.44%	17.34%	27.17%
	Parishes	29.60%	15.21%	26.09%

Table 5: Percentage of road shading by the time of day - for the whole network.

		9:00	**13:00**	**17:00**
Base configuration	Whole city	59.97%	51.25%	52.30%
	Constituencies	49.83%	49.88%	50.66%
	Parishes	48.88%	46.72%	47.48%
High traffic	Whole city	47.96%	49.80%	49.08%
	Constituencies	47.97%	48.18%	49.73%
	Parishes	47.06%	46.59%	45.21%
Maximum shade	Whole city	59.97%	57.33%	69.17%
	Constituencies	57.16%	56.43%	58.47%
	Parishes	56.83%	55.96%	58.40%

Table 6: Percentage of road shading by the time of the day - for the subset of streets improved.

5.5 CASE STUDY: TOP 3 ROUTES FOR THE WHOLE NETWORK

To qualitatively assess the results, we looked at a small sample of streets with the highest score obtained for one of the configurations. We decided to go with the base setup optimized for the whole network, with the score used being a mean score from each time of the day. The top 3 selected routes (Figure 23) are in the

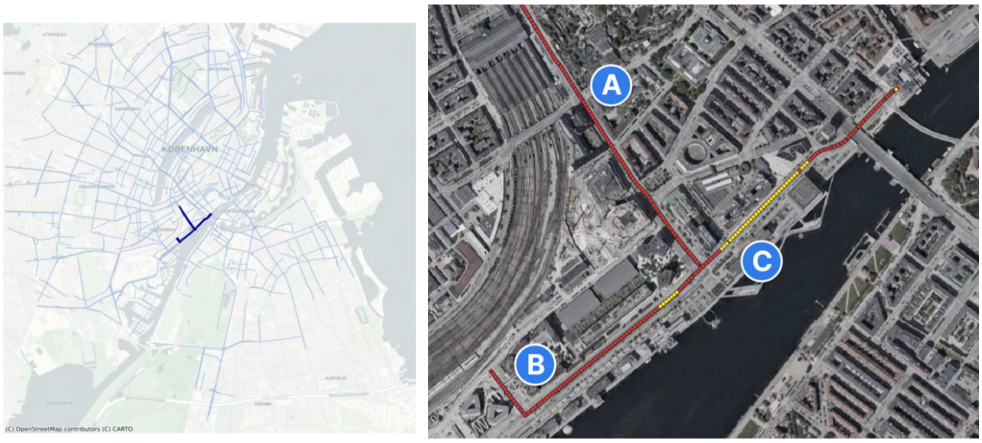


Figure 23: Top 3 streets for the case study. Shaded segments are marked as yellow.

strict city center, where one is a main road running along the canal (B, C - Kalvebod Brygge), and the other is connecting it to the Copenhagen central station (A - *Bernstorffsgade*). They are an important part of the city bicycle network in daily commuting, with the canal route being part of the *Green routes* marked as a "high traffic" street.

However, all the roads selected are poorly shaded. They have long segments available for tree planting - what is a desired situation for optimal use of the budget. There is almost no urban greenery along the selected roads and they could be potentially easily improved. Even considering possible limitations arising from not being able to plant trees in some particular places (eg. at the crossings, in places where the distance between the road and buildings is too narrow), there still is a lot of space for optimization.

Figure 24: Street-level imagery of Bernstorffsgade (a) and Kalvebod Brygge (b, c) (Copyright Google 2023)

5.6 ASSESSMENT OF MODEL PERFORMANCE

One of the main challenges of this project comes from the inconsistencies related to the tagging of spatial details in the bicycle network of Copenhagen. The bicycle network obtained from OpenStreetMap (OSM) provides us with an imperfect representation of the actual bicycle lanes' true spatial location, and it can thus heavily influence estimated shade coverage, especially from smaller structures closer to the street.

To assess the impact of the OSM street network representation on our analysis,

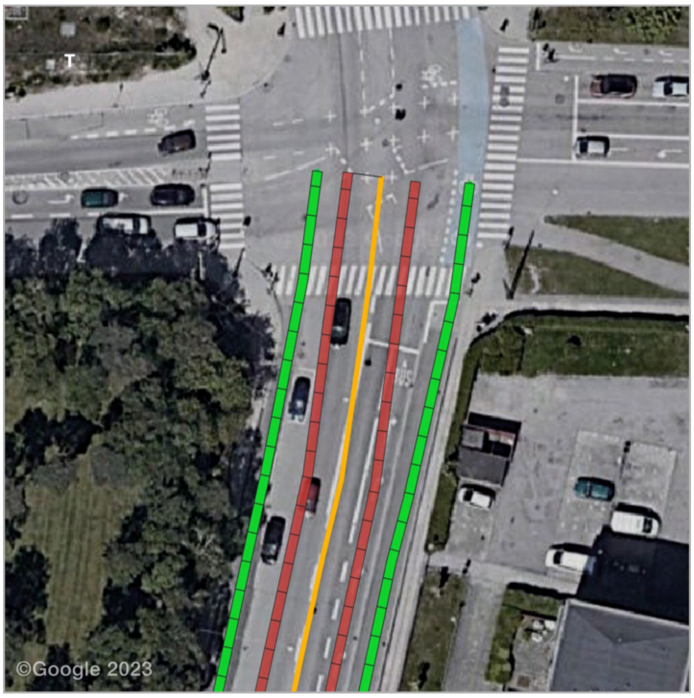


Figure 25: Adjusted bicycle paths based on alignment with Google Maps satellite imagery for ground truth comparison.
Fixed-length centerline shift
Adjusted bicycle paths

we compare shade coverage results with a human-adjusted street network. These modified paths are a subset of the bicycle network containing the 140 most busy streets, a total of 132 km. Each street segment is aligned with the most suitable path for a bicyclist using satellite imagery (from Google) as a reference (see Figure 25). This can be considered an imperfect adjustment itself, in that the imagery is only aligned within 1.5 meters of the CHM used to model the shade-casting structures.

There is a bias for the width in the subset of streets that are included in the adjusted paths, given that the streets with the most traffic are found to be wider. From a random sample of streets of the full network (N = 100), we find that the mean street width (including sidewalks) is 13.7 meters ($\sigma = 7.5$), with 17.2 meters ($\sigma = 4.1$) for the adjusted subset. There is thus a large variance in street width, and the adjusted subset is skewed towards wider streets. While this is not ideal, it is less of a concern in the context of this project, as the analysis only considers the upper 20th percentile of streets in terms of traffic density.

	Combined	9:00	13:00	17:00
Tree	▲ **13%**	▲ 21%	▲ 13%	▲ 6%
Building	▲ **8%**	▲ 15%	▲ 16%	▼ -7%
Total	▲ **10%**	▲ 16%	▲ 15%	▼ -2%

Table 7: Change in shade coverage for adjusted paths compared to shifted centerline representation.

Table 7 shows the change in estimated shade coverage for the adjusted paths compared to the shifted centerline representation. As expected, the adjusted paths result in higher shade coverage across all categories, but the aggregated differences are not in themselves enough to conclude the impact on ranking. Instead, we compare the rank of streets based on shade coverage for the two network representations by calculating Spearman's ρ (correlation coefficient). The correlation coefficient based on total shade coverage is $\rho = 0.66$, while rank based on shade only from trees results in $\rho = 0.73$. While the rankings are not identical, the mean deviation in the shade coverage between the two representations is 45% for tree-based shade and 36% for total shade. Because the score used for ranking streets in addition to shade data also contains traffic information, the impact of the street network representation is smaller. Ranking the segments using the algorithm's score formula, where traffic is incorporated (using $\alpha = 0.5$), the correlation coefficient reaches $\rho = 0.83$.

6 LIMITATIONS

A central challenge of this project evolves around the quality of the data available. When building the modeled representation of the urban landscape, including the street network, we rely on many ad-hoc data-wrangling steps, which vary in the quality of the output. This makes it difficult to be unequivocally sure of the accuracy of the results obtained.

The lack of spatial accuracy of the bicycle network is one of the weakest links in the analysis. Data on the cycling network in Copenhagen is not uniform and sometimes incomplete, and the street representation obtained provides us with an imperfect representation of the actual bike lanes' location, mainly because of inconsistent tagging in OpenStreetMap. What is more, without an accurate approximation of the width of the streets, they can be often labeled as higher in sun exposure, despite having more shade in the sections suited for bicycle traffic. While the impact of this shortcoming is limited in our case, it can generate bigger inconsistencies of shade estimate for smaller areas requiring more precision.

Another limiting factor in the analysis is the lack of accurate data on bicycle traffic. When one of our main objectives was to take real traffic into account in the process of recommending streets, the closest representation of the city's movement data we were able to obtain was the origin-destination pairs of rentable e-bikes. Interpolated paths based on such information are a good baseline for the initial analysis, but in a more precise recommendation process, this could prove insufficient. Additionally, the users of these bikes may not be necessarily representative of the general population of bicycle commuters. We are aware that the characteristics of traveling around the city with such transportation may be dominated by tourists and thus deviate from the general commuting patterns of residents of the city.

While traffic density is considered, the analysis does not take into account the directional flow of traffic. From the 400 most traveled streets, more than 25% experience a doubling in shade coverage between the morning (9:00) and afternoon (17:00). Stretches that have an asymmetrical flow of traffic during commuting hours may be more or less exposed to the sun than the analysis suggests.

7 CONCLUSION AND FUTURE WORK

There is a growing need for data-driven support for urban planning. Of particular importance here are the trees, which bring many benefits, with the shade they give in the first place. Such a task becomes even more important nowadays, with various European countries promoting green ways of transportation.

In our project, we aimed to develop a robust workflow to provide urban planners with evidence-based recommendations. Our goal was to create a tool based on open-source datasets, which will be flexible and accurate. To show the results based on real-life data, we proceed with Copenhagen as a case study. The city is recognized as one with the most extensive bicycle network, and while prioritizing planting trees in recent years, it fits perfectly for the scope of our project.

To create tree-planting recommendations, we had to process various data sources. To get a truthful representation of the urban landscape, we worked with datasets such as Danish Height Model, Google satellite photos, and OpenStreetMap. Using them, we retrieved high-quality information about the city greenery and extracted the location of separate trees. We supplemented this data with a 2.5D model of the city buildings. We used Trier API and Google API to interpolate mobility pattern of residents of the city. From OpenStreetMap, we extracted the bicycle network and adjusted it to faithfully represent the exact location of the bike lanes. In the end, we calculated how much shadow is cast on the roads at different times of the day.

Having all the data gathered, we were able to create urban planning recommendations with it. A flexible algorithm that can fit various priorities was successfully created. We tested it against multiple scenarios, both from central and local perspectives and it was observed that the results are adjusting to the requirements of the input parameters. Thanks to using only open-source data, we created a reproducible workflow that is possible to use when creating recommendations for other cities. Compared to previous work in the area, the workflow requires a small amount of manual work and can be easily generalized.

However, some possible adaptations have been left for the future. Despite parameterizing our algorithm, there are a few real-life aspects of urban planning not addressed in this thesis, such as promoting continuity of the network obtained or incorporating data about the direction of traffic on the bike lanes. One of the other possible improvements would be optimizing the street selection algorithm over maximized shadow during the whole day, not only the given hour. Future versions of the algorithm could also try to point to exact locations for suggested tree planting, instead of creating recommendations on the street level - such an approach should be made using additional information about the surroundings of the streets, to reflect possible limitations.

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