

TRANSPORT FINDINGS

Off-street Parking in 15 US Cities

Shirin Qiam¹, Lewis J. Lehe, PhD¹¹ Civil Engineering, University of Illinois Urbana-Champaign

Keywords: land-use, parking dataset, deep learning, segmentation

<https://doi.org/10.32866/001c.145256>

Findings

This study introduces a novel dataset of parking lot boundaries covering fifteen US cities. We generate this dataset using a deep learning segmentation model described in Qiam et al. (2025), and a subsequent post-processing workflow. The dataset, publicly available in shapefile format, enables spatial analysis of parking land use at both inter- and intra-city levels. To estimate the share of off-street land used for off-street parking, we link these polygons with tax parcel datasets, in order to exclude streets and public sidewalks. Off-street surface parking accounts for as little as 3.4% of parcel land in Oakland and as much as 10.7% in Anaheim, with central business districts ranging from 2.3% in Boston to 31.7% in Tulsa.

1. Questions

It is obvious that off-street parking occupies a substantial share of the land in U.S. cities, but it is hard to say precisely how much. Academic studies (e.g., Hoehne et al. 2019) have made estimates by inference from zoning codes and other rules. Garber et al. (2024, 2–3) provides a review. Recently, an organization called the Parking Reform Network (Carpenito 2023) has measured off-street parking more directly, in downtowns, by manually editing and supplementing polygons from OpenStreetMap (OpenStreetMap 2025). Similarly, this study introduces a novel dataset of parking lot boundaries for fifteen U.S. and a methodology to create such datasets using a deep learning model and post-processing techniques. It is hoped that this dataset will be useful to answering research questions involving surface parking. As an example, we use this dataset to answer: “How does the quantity of land used for off-street surface parking lots, and the share of tax parcel land devoted to them, vary between and within cities?”

Regarding the presence of “tax parcels” in this question, these¹ are of interest as a rough measure of land devoted to surface parking that could be used otherwise (e.g., for housing, retail or schools). Millard-Ball (2022, 31) estimates land used for streets (“including sidewalks, landscaping, and the road-way”) by the voids between parcels. Inspection of tax parcel maps showed that parcels do exclude most streets, as well as sidewalks and bodies

¹ Cook County (containing Chicago) provides a useful map at <https://maps.cookcountyil.gov/taxmapviewer/> where readers can see the nature of US tax parcels.

of water. While imperfect, we think that parking lots' share of *parcel land* measures their “opportunity cost” (Gabbe, Osman, and Manville 2021) better than their share of *all land* would, as the latter includes so much land that would be difficult or undesirable to develop.

2. Methods

The steps used to generate the parking lot dataset are as follows:

1. Google Maps satellite tiles were downloaded for all land within the boundaries of the cities in [Figure 1](#). These were selected because (i) they have accessible parcel data; and (ii) lie in different regions of the US. City limits are from the U.S. Census Bureau's TIGER dataset (USCB 2024). We use city limits because laws such as minimum parking requirements (Shoup 1999) are typically applied at the city level.
2. The satellite tiles were fed into the deep learning model described² by Qiam, Devunuri, and Lehe (2025), which classifies each pixel in each tile as either parking or background. This model achieves a pixel-wise accuracy of up to 96.3% in test data. The deep learning model is available at <https://huggingface.co/UTEL-UIUC/SegFormer-large-parking>.
3. The predicted parking pixels were merged into GeoJSON polygons.
4. The Overpass Turbo service (<https://overpass-turbo.eu/>) was used to extract OpenStreetMap (2025) polygons of (a) airport aprons, (b) railroad land, and (c) parking garages. The model sometimes misclassifies (a) and (b) as parking. Regarding (c), garages are not surface parking—the study's focus.
5. We used the ArcGIS polygon simplification tool to reduce the number of vertices in the parking polygons. This did not produce any noticeable changes in their shapes or the statistics, but it makes the dataset much smaller and easier to adjust.

² While Qiam, Devunuri, and Lehe (2025) presents a manually-annotated training dataset of 12,000 mask/tile pairs used to train the model, that dataset is different than the one used here. This study's dataset covers different titles, consists of model predictions, and uses different post-processing steps.



Figure 1. Parking Lot distribution for 15 U.S. cities. Note that the scale varies across cities.

6. Manual correction in ArcGIS was used to fix major mistakes and delete polygons of paved surface used for cargo handling or industry.

The code that executes steps (i)-(iv) is available at <https://github.com/UTEL-UIUC/parking-lot-mapping-tool>.

For the parcel share calculations, tax parcels were obtained from the county datasets. An online appendix at <https://github.com/UTEL-UIUC/ParkingLot-Statistics> provides links to the data sources used. Finally, we delete any parking polygons lying outside parcels—which were rare, very small and obviously erroneous.

To investigate how parking varies *within* cities, we assign each city a “downtown point” coordinate by choosing a point lying within the area labeled as “downtown” on Google Maps that seems to be central or focal. Duranton and Puga, Appendix A (2023, Appendix A) do the same. The exact point chosen is a judgement call, as there exist no Platonic city centers.

3. Findings

An interactive ArcGIS map showing the parking polygons, downtown points, and city limits is available at <https://www.arcgis.com/apps/dashboards/f51defadb58e4a6fb7c219b6dc50f5bb>. The parking lot dataset generated is available in shapefile format at <https://huggingface.co/datasets/UTEL-UIUC/Parking-Lot-15cities>. [Figure 1](#) shades parking areas as blue and parcel areas as gray. The first column of [Table 1](#) shows the total share of parcel land used for surface parking. Oakland has the least surface parking share overall (3.4%), while Anaheim has the highest (10.7%). Columns 2-4 of [Table 1](#) present the share of parcel land used for off-street surface parking lots in three zones: a CBD area (<1 km from the downtown point), a middle area (1-5 km from the downtown point), and an outer area (beyond 5 km). Tulsa’s CBD exhibits the highest share of parking (31.7%), and Boston’s the lowest (2.32%). The last column of [Table 1](#) shows the how far, on average, a square meter of surface parking is from the downtown point. This average is obtained by taking a weighted average of the distance of each parking lot’s centroid to the downtown point, where each parking lot’s weight is its area.

[Figure 2](#) presents the cumulative parking area (in square kilometers) that lies within a certain distance from the downtown point, up to 20 km. Phoenix, Dallas and Indianapolis have the highest area of parking within 20 km of downtown, at around 60 km². A common approach to analyzing spatial gradients of urban variables is to create concentric rings around the downtown point and analyze how the variable of interest varies across them (e.g., Jiao 2015). [Figure 3](#) shows the percentage of parcel land in each ring used for off-street surface parking, with each ring being 1 km thick. Generally, the share of parking is highest close to downtown and declines overall with distance, but some cities (e.g., Oakland, Memphis, Tulsa) have a notable second peak farther out. By inspecting maps, we saw this second peak typically corresponds to rings containing shopping malls and car dealerships.

Beyond analyzing the distribution of parking lots, further research could use this study’s dataset to investigate relationships of cause-and-effect. Possible research topics include: (i) the influence of land-use regulations; (ii) the

Table 1. Parking Share of Parcel Land (%) by City

City	Total	CBD (< 1km)	Middle (1-5km)	Outer (> 5km)	Avg. Dist (km)
Anaheim	10.7	9.6	15.1	7.7	5.5
Atlanta	5.5	19	8.8	4.6	7.1
Boston	5.1	2.3	7.2	4.2	6.3
Chicago	6.1	2.9	9.6	5.9	13.2
Dallas	7.7	20.5	10.8	7.4	12.2
Indianapolis	6.9	19.9	11.1	6.5	11.2
Los Angeles	5.7	22.3	13.8	5.2	21.4
Memphis	7.4	17.7	10.4	7.2	14.3
Minneapolis	7.0	14.1	10.3	3.5	4.0
Oakland	3.4	10.3	4.9	2.9	6.9
Phoenix	8.3	15.6	17.7	7.7	13.2
Riverside	6.4	13.6	8.7	5.4	6.8
San Diego	4.8	9	5.2	4.8	16.9
Seattle	5.1	8.1	6.4	4.7	7.1
Tulsa	7.3	31.7	7.0	7.2	10.8

value of land occupied by surface parking lots, as investigated for streets by Millard-Ball (2022) and Guerra, Gilles, and Ma (2025); and (iii) the association of parking and the urban heat island effect (Onishi et al. 2010). The methodology could also be used to generate similar datasets for other cities, or look at metropolitan areas rather than city boundaries.

Submitted: September 12, 2025 AEDT. Accepted: October 07, 2025 AEDT. Published: October 16, 2025 AEDT.

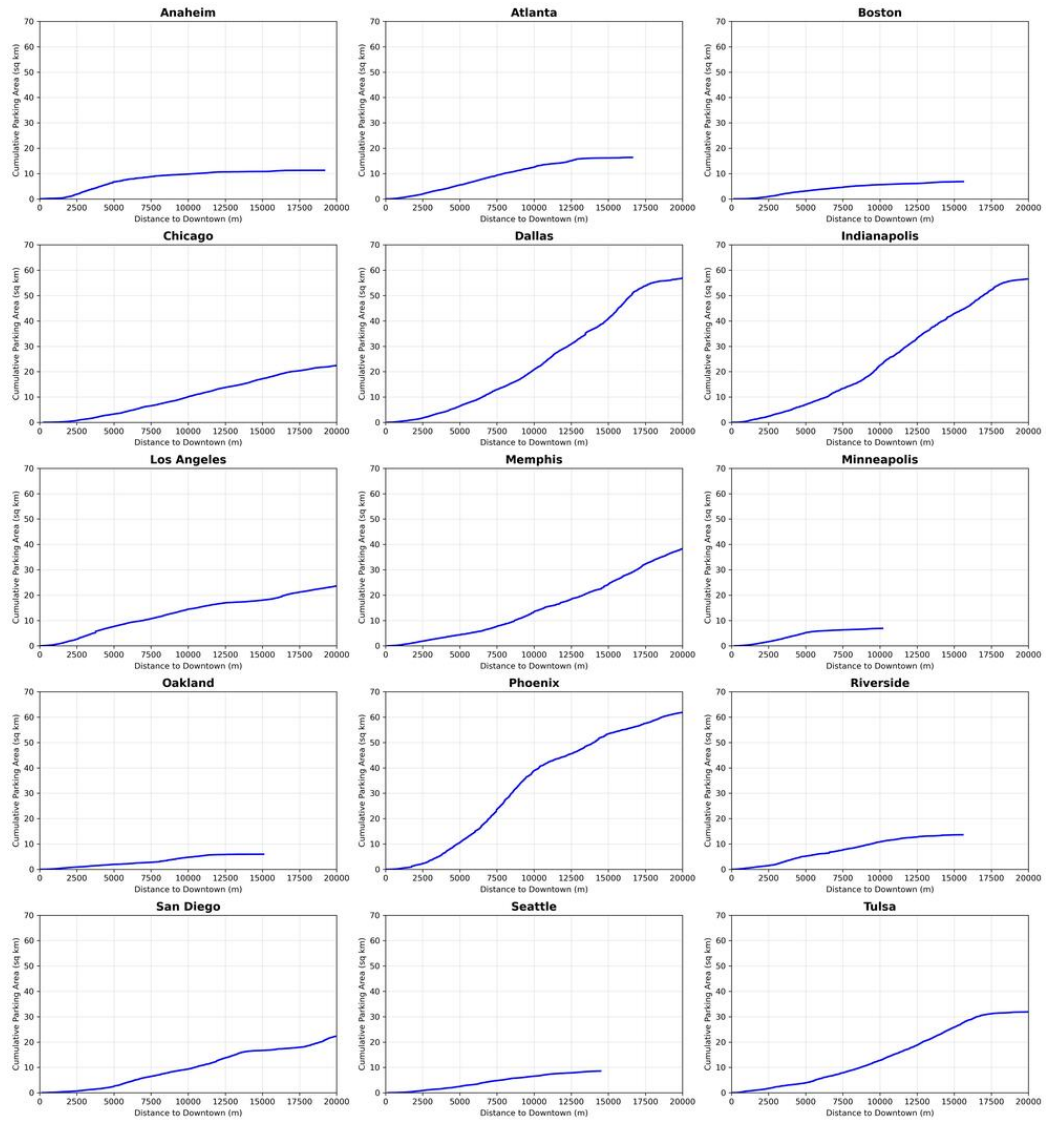


Figure 2. Cumulative parking area by distance from downtown

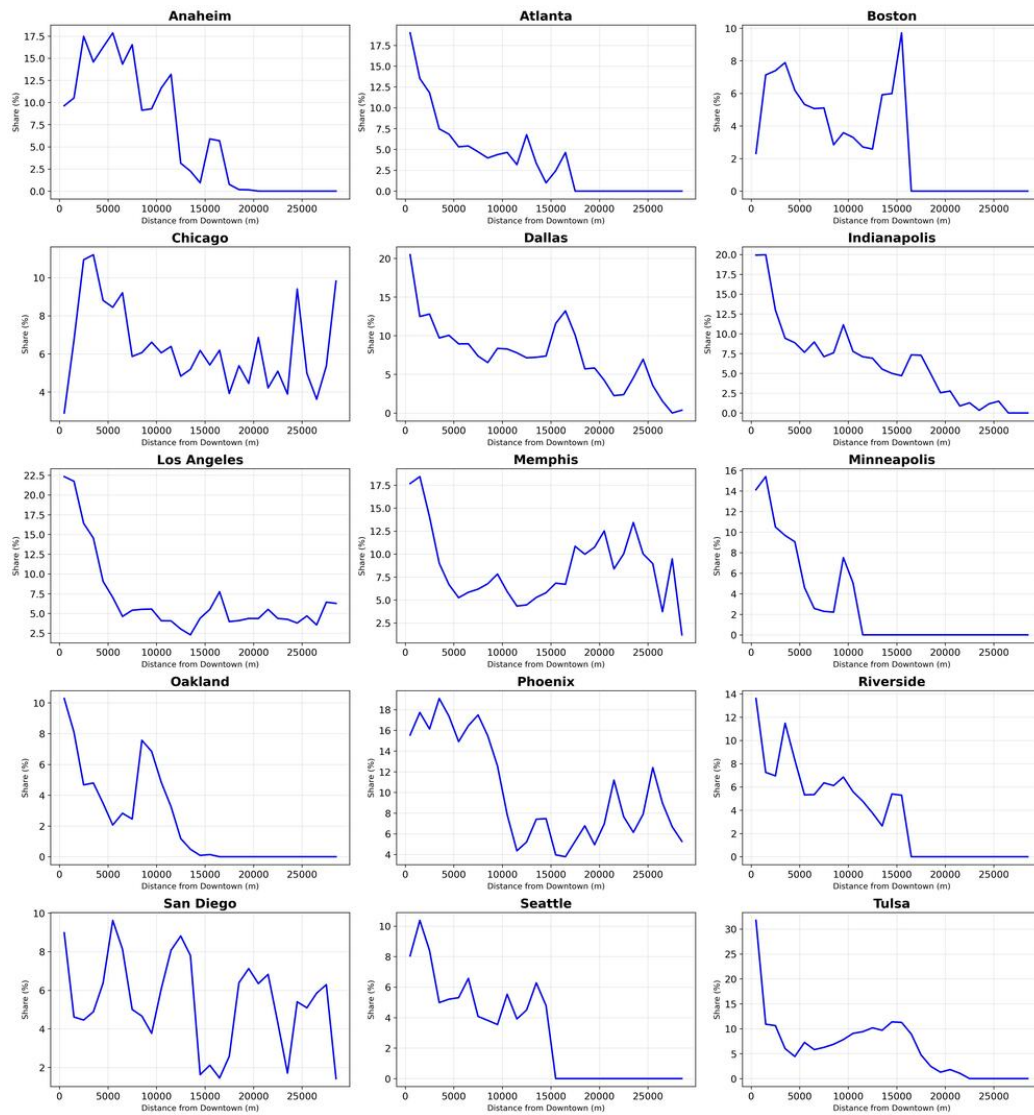


Figure 3. Cumulative parking area by distance from downtown



This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CCBY-SA-4.0). View this license's legal deed at <https://creativecommons.org/licenses/by-sa/4.0> and legal code at <https://creativecommons.org/licenses/by-sa/4.0/legalcode> for more information.

REFERENCES

- Carpenito, Thomas. 2023. "Parking Lot Map. Parking Reform Network."
- Duranton, G., and D. Puga. 2023. "Urban Growth and Its Aggregate Implications." *Econometrica* 91 (6): 2219–59. <https://doi.org/10.3982/ECTA17936>.
- Gabbe, C., T. Osman, and M. Manville. 2021. "The Opportunity Cost of Parking Requirements." *Journal of Transport and Land Use* 14 (1): 277–301. <https://doi.org/10.5198/jtlu.2021.1758>.
- Garber, Michael D., Tarik Benmarhnia, Jacob Mason, Emily Morales-Zamora, and David Rojas-Rueda. 2024. "Parking and Public Health." *Current Environmental Health Reports* 12 (1): 2. <https://doi.org/10.1007/s40572-024-00465-4>.
- Guerra, Erick, Duranton Gilles, and Xinyu and Ma. 2025. "Urban Roadway in America: The Amount, Extent, and Value." *Journal of the American Planning Association* 91 (1): 102–16. <https://doi.org/10.1080/01944363.2024.2368260>.
- Hoehne, C. G., M. V. Chester, A. M. Fraser, and D. A. King. 2019. "Valley of the Sun-Drenched Parking Space: The Growth, Extent, and Implications of Parking Infrastructure in Phoenix." *Cities* 89:186–98.
- Jiao, Limin. 2015. "Urban Land Density Function: A New Method to Characterize Urban Expansion." *Landscape and Urban Planning* 139 (July):26–39. <https://doi.org/10.1016/j.landurbplan.2015.02.017>.
- Millard-Ball, Adam. 2022. "The Width and Value of Residential Streets." *Journal of the American Planning Association* 88 (1): 30–43. <https://doi.org/10.1080/01944363.2021.1903973>.
- Onishi, A., X. Cao, T. Ito, F. Shi, and H. Imura. 2010. "Evaluating the Potential for Urban Heat-Island Mitigation by Greening Parking Lots." *Urban Forestry & Urban Greening* 9 (4): 323–32.
- OpenStreetMap. 2025. "Parking Data from OpenStreetMap."
- Qiam, Shirin, Saipraneeth Devunuri, and Lewis J. Lehe. 2025. "A Pipeline and NIR-Enhanced Dataset for Parking Lot Segmentation." In *2025 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, 1227–36. <https://doi.org/10.1109/WACV61041.2025.00127>.
- Shoup, Donald C. 1999. "The Trouble with Minimum Parking Requirements." *Transportation Research Part A: Policy and Practice* 33 (7): 549–74. [https://doi.org/10.1016/S0965-8564\(99\)00007-5](https://doi.org/10.1016/S0965-8564(99)00007-5).
- USCB. 2024. "United States Census Bureau, 2024 TIGER/Line Shapefiles (Machine Readable Data Files). U.S. Department of Commerce."