Empowering OpenStreetMap (OSM) Network Data for Transportation Applications: A Case Study on the Impact of Congestion on Accessibility

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Abstract

OpenStreetMap (OSM) data is a valuable resource for various transportation, traffic, and planning applications. However, OSM network data lacks operating traffic speed information, which is critical for transport planning and operations. Addressing this shortcoming, this study leverages proprietary data (to serve as ground truth) and uses exogenous, open-source variables such as transport infrastructure, land use, demographic information to predict operating traffic speeds on OSM networks. Three machine learning models were tested, and separate models were estimated for OSM links with and without speed limit information in the Denver metropolitan region. Among the models tested, XGBoost performed best, with mean absolute errors of 3.27 and 3.62 mph, respectively, for links with and without speed limits. The developed models accurately predicted traffic speeds for different hours and days of the week when compared with ground truth data. Using these predicted speeds, accessibility scores were computed for the Denver region for different time periods using the Mobility Energy Productivity (MEP) metric. Results show that congestion-adjusted accessibility is significantly lower compared to accessibility calculated using free flow speeds. Specifically, weekday evening hours saw a 42% drop in accessibility due to reduced speeds, particularly around downtown Denver. Across the Denver metro, approximately half as many opportunities and jobs are accessible in under 20 minutes by car during the evening peak period relative to free flow conditions. The methodology presented here enriches OSM networks, making them useful for an even broader range of transportation applications.

Keywords: OpenStreetMap (OSM), congestion, accessibility, Mobility Energy Productivity (MEP), temporal variations.

1. Introduction

It is often difficult to think of auto (aka personal vehicle) travel without mentioning the word "congestion". Whether it is regular commuters or occasional travelers, everyone has fallen peril to the impacts of traffic congestion at one point or another. Traffic congestion can take two forms. The first is recurring traffic congestion which creates the universally hated morning and evening peak periods where vehicles slow down or even come to a standstill. The second form of congestion is termed as non-recurring congestion, which can be created by unplanned events such as a crash, or a natural disaster. While it is extremely difficult to predict the reason or occurrence of non-recurring traffic congestion, it is straightforward to understand and forecast recurring congestion in a city. In fact, understanding and accounting for increased travel time (due to traffic congestion) is critical for urban planning, traffic operations, and accessibility computations. Particularly, in the context of accessibility, spatial and temporal access to various opportunities such as employment centers, hospitals, and other key destinations are greatly impacted by congestion. Neglecting the impact of congestion can result in a pseudo-optimistic and inaccurate portrayal of travel performance measures, thereby undermining the efficacy of urban planning and policy interventions.

Accessibility scores serve as performance measures for the connectivity of a city's transportation system indicating how easily people can access essential opportunities such as food, healthcare, jobs, and recreation in various time of the day, and from various locations. However, traditional access calculations have relied on static travel time assumptions (Kwan, 2013), failing to capture the dynamic nature of traffic congestion (and in turn access) throughout the day. Real-world traffic conditions are fluid, with congestion levels fluctuating based on the time of day, day of the week, and various other factors (Chiabaut & Faitout, 2023). This variability may significantly impact accessibility scores, rendering static models insufficient for accurate analysis. Thanks to the advancement in data collection technologies, it is now easier than ever to obtain operating (or observed) speed data collected from mobile applications and vehicle probes to help with an accurate portrayal of congestion and accessibility in a city. However, such data comes with a high cost which many cities or planning agencies would find difficult to afford. Also, speed data provided by commercial vendors is often tagged with a 'proprietary' road network, which needs to be acquired separately (or as an add-on) on top of observed operating speed data purchases. In the context of computing access to opportunities, a geospatial layer depicting the coordinates of various opportunities needs to be acquired, again, at a cost from commercial vendors.

OpenStreetMap (OSM) provides an excellent alternative to proprietary data to gain a comprehensive understanding of a city's road network and geography. OSM is a crowdsourced map of the world, which is updated on a continuous basis, and provides comprehensive geospatial data. OSM data has been used for diverse applications including transport and urban planning studies (Felício et al., 2022; McArthur & Hong, 2019). With its extensive and detailed geographical data, OSM provides information for mapping and analyzing urban infrastructure, road networks, and points of interest. As such, the information included in OSM presents a perfect substitute to proprietary data for many transportation applications including accessibility calculations. However, a critical shortcoming of OSM data is that it only has information on 'posted speeds' (or speed limits) at the link level. While OSM's speed limits can serve as a proxy

for accessibility calculations (Gil, 2015), they lead to oversimplified representations of travel times and often fail to reflect realistic travel conditions. This discrepancy can lead to an artificially inflated depiction of accessibility in a city, particularly during congested times of the day. Adding temporally varying operating speed information to universally available OSM networks can greatly enhance the utility of this comprehensive and free to use data source.

Addressing this need, this study develops a methodology to predict realistic operating speeds across an OSM network while accounting for congestion. The study has two primary objectives: first, to develop models that predict operating (or congestion-adjusted) speeds on a city's OSM network; and second, to use the predicted speeds to analyze accessibility scores across various times of the day and days of the week. The proposed methodology employs three machine learning algorithms—random forest, extreme gradient boosting, and multi-layer perceptron neural network —along with linear regression to build models for predicting operating speeds. These models leverage historical traffic speed data from a reliable commercial vendor, OSM network and point of interest data, and US Census population and employment data to generate realistic speed estimates for different time periods. By incorporating these predictions into the OSM network, the study aims to create a more accurate representation of travel times that reflect real-world conditions. To demonstrate the advantage of adding operating speeds to OSM networks, drive accessibility scores are computed for morning, afternoon, and evening time periods on both weekdays and weekends using congestion-adjusted operating speeds. This analysis illustrates how temporal variations in traffic speeds and congestion affect accessibility, providing valuable insights for urban planners and policymakers.

The remainder of this paper is organized as follows. Section 2 provides a review of relevant studies and summarizes the gaps in research that this study seeks to address. Section 3 outlines the data used for congestion prediction as well as accessibility calculations, while Section 4 describes the models used and results obtained to predict observed speeds in the OSM network. Section 5 discusses the accessibility metric used in the study and presents accessibility scores calculated for different hours and days using the congestion-adjusted speeds. The final section presents the conclusions, implications, and limitations of the study.

2. Literature Review

OpenStreetMap (OSM) has emerged as an invaluable resource in transportation and urban planning due to its extensive, crowdsourced mapping data. The OSM network layer has been effectively utilized in various studies. For instance, Mobasheri et al. (2017) evaluated OSM's network suitability for routing services for individuals with limited mobility. Zielstra et al. (2011) used it to enhance pedestrian accessibility analyses for transit, and Wasserman et al. (2019) validated its accuracy in predicting traffic stress levels for bicycle route planning. Similarly, the OSM point of interest (POI) layer has been employed in several transportation applications, including calculation of location attractiveness in travel demand models (Klinkhardt et al., 2021) and extracting the availability of signalized intersections (Qu et al., 2024). Despite these capabilities, the OSM network has notable shortcomings, such as the absence of operating speed information and incomplete observations for attributes like speed limits, number of lanes, and availability of bike lanes. Enriching OSM with comprehensive operating speed data and other critical attributes can significantly enhance its utility for various

transportation applications. This study focuses on enhancing OSM network data with temporally varying link-level operating speeds.

There have been some past efforts to predict operating speeds on road links. Himes et al. (2013) predicted operating speeds on rural two-lane highways using least squares regression models based on geometric design features and traffic flow characteristics. Himes and Donnell (2010) employed the simultaneous equation model to analyze traffic flow characteristics on multilane highways, finding that the posted speed limit should be treated as an exogenous variable in operating speed prediction models. Alomari et al. (2022) demonstrated the value of machine learning models in predicting free flow speeds using various geometric, traffic, and pavement condition variables. In summary, these studies primarily utilized localized traffic volume and geometric characteristics for predicting operating speeds. However, a significant gap remains in predicting link-level operating speeds within the OSM network. Keller et al. (2020) attempted to address this gap by developing machine learning models to predict operating speeds in the OSM network using several OSM network geometry attributes for rural highways in Chile and Australia. Despite this progress, the models face spatial transferability issues due to the use of localized features, such as the latitude and longitude of road links. To ensure the spatial transferability of observed speed prediction models, features must be transferable and derived from open-source, readily available data. Transportation infrastructure and land use features (both readily available in OSM) can effectively predict operating speeds, especially in urban conditions. This leads to the first objective of this study: enhancing the attributes of open-source OSM data by enriching it with operating (congestion-adjusted) speeds for different times of the day and days of the week.

In the context of urban accessibility, traditional calculations have relied on static travel time assumptions (e.g., Chen et al., 2017; Lucas et al., 2016), considering access to opportunities as fixed in time. Studies have shown that this assumption often results in higher accessibility estimates than actual conditions (Zhang et al., 2018). However, the time dimension is inherent to accessibility, as the time required to reach opportunities varies temporally, especially in urban areas due to congestion. The consideration of temporal variations in accessibility calculations requires temporally varying operating speeds. Li et al. (2011) demonstrated that accessibility scores vary temporally when supplemented with operating speeds from floating car data. More recently, speed data from entities like Google, INRIX, and TomTom have gained popularity. Moya-Gómez and García-Palomares (2017) used TomTom speed data to investigate the impact of congestion on automobile accessibility in eight European metropolitan areas, revealing significant temporal variations, with cities like London, Paris, and Rome experiencing the highest impacts during peak periods. Owen and Murphy (2019) measured job accessibility by automobile in the 50 largest U.S. metropolitan areas, comparing access available at 4 AM (free flow conditions) and 8 AM (congested conditions) to assess congestion impacts. They found that central city workers face less accessibility loss compared to those from the outskirts due to a *ring of congestion* surrounding many cities. These observations underscore the need to understand the impact of temporally and spatially varying congestion on accessibility. This leads to the second objective of this study: quantifying the impact of congestion-adjusted operating speeds on a city's accessibility using the enhanced open-source OSM network dataset.

In summary, the objective of this study is two folds: (a) to develop a methodology to predict operating speeds for various times of the day and days of the week and enrich the OSM network with predicted speeds, and (b) to leverage the enriched OSM dataset to investigate the impact of congestion on urban accessibility across different time periods. The study focuses on the Denver metro area, with the potential for the proposed approach to be scaled up for a national-level application.

3. Data

3.1 Study Area and Data Sources

The study area selected for this analysis is the Denver metro region (shown in **Figure 1**), which has a population of 2.9 million individuals, residing in 1.3 million households (Census Reporter, 2022). Home to the Rocky Mountains, Denver metropolitan region attracts a significant number of visitors across the year due to the wide range of outdoor recreational opportunities it offers. Hence, the region sees congestion on weekdays (that is typical for most American cities), as well as weekends (worsened due to visitor travel). The downtown economic district of Denver is surrounded by vibrant suburbs such as Englewood, Littleton, and Centennial on the south, and mountainous suburbs such as Golden on the west, with cities such as Westminster and Thornton appearing on the north. Eastern part of Denver comprises as few suburbs but more importantly has the Denver Internation Airport which is the sixth busiest airport in the country (Fly Denver, 2023). The radial nature of the city's landscape and road network naturally create congestion problems for morning as well as evening commutes. Particularly, the triangle formed in area of I-25, I-70, and I-225 sees heavy congestion during the evening rush hour, resulting in lost time, fuel, and reduced access for residents as well as visitors.

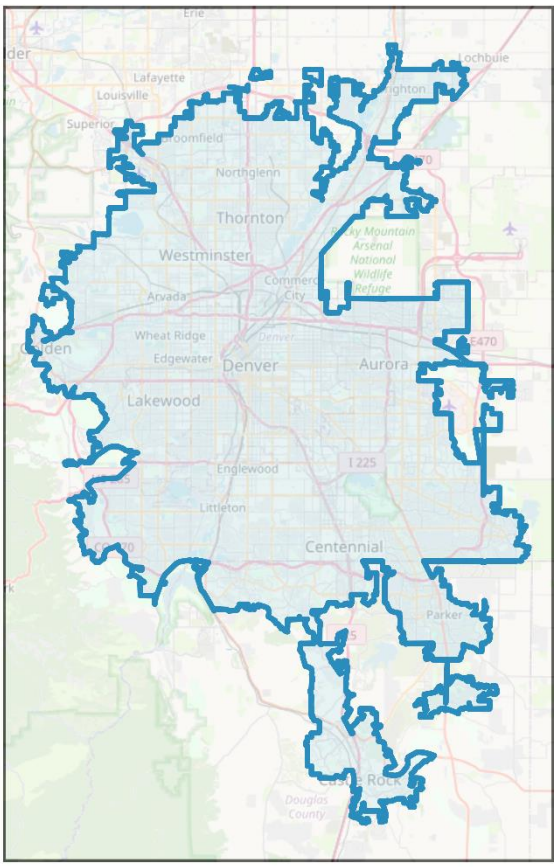


Figure 1: Study area: the Denver metro region.

The data sources leveraged for this study include OpenStreetMap (OSM) for road network, land use, and traffic features; a commercial vendor for historical traffic speed data; and the US Census Bureau for population and employment density. The commercial vendor collects real-time probe data from navigation devices, in-dash systems, and mobile applications and uses this data to derive historical traffic information. For this study, the vendor provided historical traffic speeds for roadways at an hourly resolution, referred as operating speeds hereafter. Median link-level operating speeds were obtained for a representative weekday (Wednesday) and weekend (Sunday) for 8-9 AM (morning), 10-11 AM (afternoon), and 5-6 PM (evening) based on data for the whole year of 2022. Population and employment density estimates were derived from the 2018-2022 American Community Survey estimates at the Census block group level (U.S. Census Bureau, 2022a, 2022b). Road network data, including roadway characteristics and speed limits, was sourced from OSM. Additionally, OSM's point of interest (POI) data was leveraged for traffic features (traffic signals, stops, streetlamps, and pedestrian crossings) and land use opportunities (recreational, medical, school/religious, meals, and shopping/errands). Both the OSM network and POI data were queried using the OSMnx package (Boeing, 2024) in Python.

For the road network, only links eligible for driving were selected. Based on the road class, the following OSM *highway* key values were considered as drive-eligible: *motorway, motorway_link, trunk, trunk_link, primary, primary_link, secondary, secondary_link, tertiary,*

tertiary_link, residential, service, track, road, or *unclassified.* To identify traffic features, objects tagged with the *highway* key values of *traffic_signals, crossing, street_lamp,* or *stop*, as well as the *crossing* key with a value of *traffic_signals* were queried. If a traffic signal is not mapped separately from a crossing (OpenStreetMap contributors, 2024), a point was included as both a traffic signal and a crossing. Informal crossings were excluded from the analysis. For the land use opportunities, several OSM tags and values related to recreational, medical, school/religious, meals, shopping/errands opportunity types were queried.

3.2 Data Preparation and Descriptive Statistics

The queried data pertaining to road network, land use, traffic features, and operating speeds was prepared for the model estimation. First, the OSM network was processed using the OSMnx package, which included consolidating the graph and ensuring its routability. In instances where an OSM link had multiple highway tags, the first drive-eligible class was selected as the roadway class. Second, the network from the commercial vendor was spatially integrated with the OSM network using techniques such as buffering, spatial intersection, and heading alignment to map operating speeds onto the OSM road links. The integration process involved the following key steps:

1. Buffering: A 5-meter buffer was generated around each OSM link, creating a spatial boundary within which proprietary data links were considered for potential matching.
2. Spatial Intersection: Links from the proprietary dataset that intersected the OSM buffers were identified. This spatial intersection yielded a set of proprietary network links potentially matched with OSM network segments.
3. Heading Alignment: To ensure directional consistency, only proprietary links whose mean headings deviated by no more than 45 degrees from the corresponding OSM links were retained. This filtering step improved the accuracy of matching links by direction of travel.
4. Speed Calculation: For each OSM link, the operating speeds of the intersecting proprietary links were averaged. The averaging process was weighted by the lengths of the proprietary links, giving more influence to longer links in determining the final speed.

This approach enhanced the OSM network by incorporating speed data from the commercial vendor for various times of day and days of the week. Additionally, temporal indicator variables were created to represent the speeds during different time periods relevant to the analysis. Finally, A 0.5-mile buffer was applied around the OSM road network to obtain the density measures for population, employment, land use characteristics, and traffic features.

The prepared dataset comprised of 434,959 links, covering 39,566 miles in the Denver metro region. **Table 1** details the distribution of these links and miles across different road classes. More than one-third of the roadway miles were residential and service roads which constitute a significant portion of the road network in the region. Further, about 79 percent of links by length had a missing speed limit in the OSM dataset. It is interesting to note that this percentage is lower for secondary (27%) and primary (26%) road classes, and 0% for motorways.

Table 1. OSM road class distribution in the Denver metro region.

OSM road class	# of links	Length (miles)	% of missing speed limit (by length)	Highway tags
Motorway	2,365	854	0%	motorway, motorway_link
Trunk	1,238	206	26%	trunk, trunk_link
Primary	11,120	1,158	27%	primary, primary_link
Secondary	15,940	1,632	39%	secondary, secondary_link
Tertiary	42,149	3,507	63%	tertiary, tertiary_link
Residential	170,578	15,606	83%	residential
Service	178,792	15,465	98%	service
Other	12,777	1,138	0%	track, road, unclassified
Total	**434,959**	**39,566**	**79%**	

To correct for erroneous operating speeds (e.g., due to too few observations) in the proprietary data, the median speed of each link was ensured to be no greater than 10 mph over the speed limit, or no greater than 5 mph over the maximum speed limit of the road class if the link's speed limit was missing. After this correction, 17% of the operating speed values were missing, and 23% had speeds lower than 10 mph; these entries (and corresponding links) were subsequently removed from the dataset. **Figure 2** displays the median speed limits retrieved from OSM alongside median operating speeds from proprietary data for different road classes for various hours and days. The figure highlights speed variations across different time periods and their deviations from the speed limits. Weekday morning and evening hours have lower median operating speeds, presumably due to rush hour traffic during those times. On the flipside, weekend (Sunday) mornings (8-9 am) see the highest median operating speeds as this is the time when most of the households are spending time in their homes. The variation in operating speeds from the proprietary data is consistent across road classes, and in-line with speed limit information from OSM, which demonstrates the veracity of the ground-truth data used for this analysis. The 'Other' road class category exhibits higher median operating speeds across all time periods compared to residential and service classes, as it includes all unclassified links and those with missing highway class tags in OSM, which may encompass higher-function road classes. Variations in operating speeds observed across road classes and day-hour pairs underscores the importance of day- and hour-specific accessibility calculations and their divergence from speed limit-based accessibility metrics.

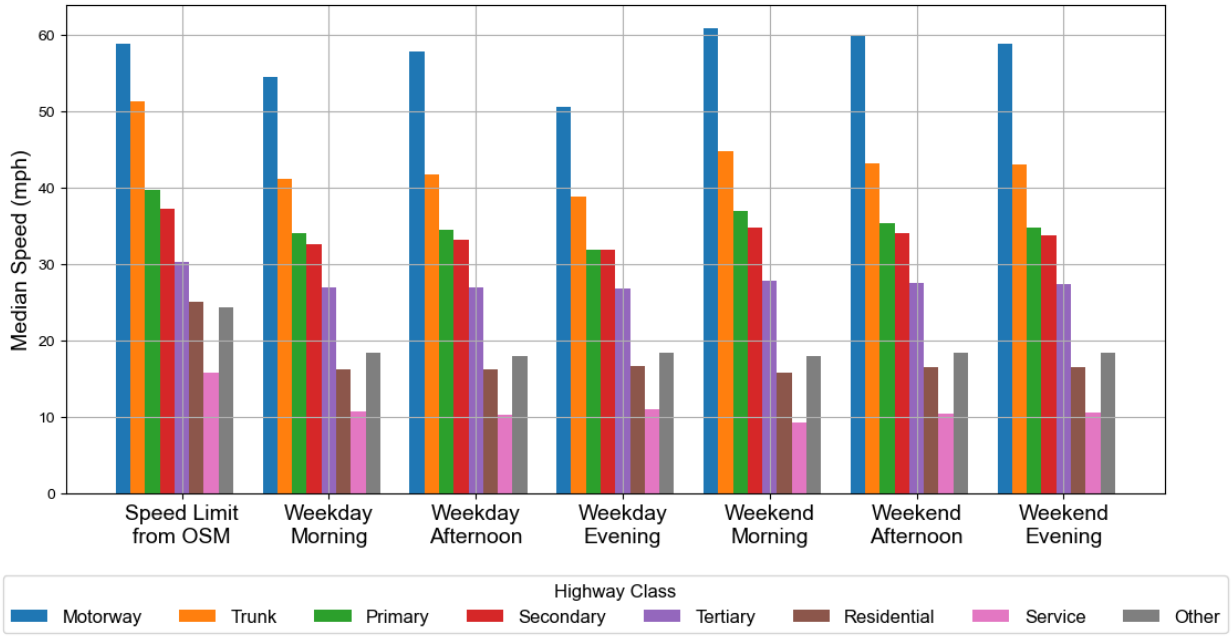


Figure 2: Median speed limits and observed speeds for various highway classes across different hours and days within the study region.

The Denver metro boundary had a population density of 2,264 per square mile and an employment density of 1,243 per square mile in 2022. The query of land use opportunities yielded 5,241 meal opportunities, 4,246 school/religious opportunities, and 19,986 recreational opportunities, 1,100 medical opportunities, and 11,669 shopping/errands opportunities. Additionally, 13,713 traffic signals, 9,139 stops, 35,616 streetlamps, and 60,003 pedestrian crossings were identified within the study region. The prepared dataset included densities of these features around each road link, obtained through using a 0.5-mile buffer. Within 0.5 miles of network links, the average population and employment densities were 2,796 and 1,576 per square mile, respectively. Among different land use opportunities, recreational opportunities had the highest average density (21 per square mile) followed by shopping/errand opportunities (18 per square mile). Medical opportunities had the lowest average density of 1.7 per square mile. In terms of traffic features around 0.5 mile of network links, pedestrian crossings had the highest density of 85 per square mile, followed by streetlamps at 47 per square mile. The mean densities of traffic signals and stops were 20 and 14 per square mile, respectively. It is encouraging to see a higher density of traffic signals and stops around road links which can serve as a proxy measure for good traffic control in the region.

4. Operating Speed Prediction

4.1 Model Development

The prepared dataset was used to develop models that predict operating speeds for different hours and days for OSM network links in the Denver metro region. The exogenous attributes considered in the models can be categorized into the following groups:

1. **Transport Infrastructure**: Speed Limit, Road Class (Motorway, Trunk, Primary, Road Class: Secondary, Tertiary, Service, Other), Traffic Signal Density, Traffic Stop Density, Pedestrian Crossing Density, and Streetlamp Density.
2. **Demographic Characteristics**: Population Density, and Employment Density.
3. **Land Use Features**: School/Religious Opportunity Density, Medical Opportunity Density, Shopping/Errands Opportunity Density, Recreational Opportunity Density, and Meals Opportunity Density.
4. **Temporal Features**: Day (Weekday, Weekend), and Hour (Morning, Afternoon, Evening).

Each of the variables used in model estimation are hypothesized to have a distinct impact on operating speed prediction. For example, higher population density can be a predictor of reduced speeds in the evening peak hour driven by workers returning home during that time period. Higher density of traffic signals on the other hand can be conjectured to contribute to lower speeds across the day, as traffic signals are typically installed in higher numbers in areas with heavy traffic. Since the dataset had a distinction based on the availability of speed limit feature (with 79% of the links missing this information), two models were developed: one including speed limit and the other excluding it. Three machine learning algorithms namely random forest, extreme gradient boosting (XGBoost), and multi-layer perceptron (MLP) neural network were used for predicting operating speeds on OSM links. A linear regression model was estimated and used as a baseline for comparison.

Random forest, an ensemble learning method with multiple decision trees, was utilized to improve predictive performance and reduce overfitting (Rigatti, 2017). XGBoost, an optimized gradient boosting algorithm, was chosen for its robustness and efficiency in handling large datasets with complex interactions (Chen, 2016). The MLP neural network, a type of artificial neural network, was selected for its ability to recognize complex patterns and relationships within the data (Popescu, 2009). The dataset was split into training (80%) and testing (20%) sets. Each of the models were trained on the training dataset, with hyperparameter tuning performed using grid search where applicable. For instance, in the case of Random Forest and XGBoost, grid search was utilized to identify the optimal combination of hyperparameters that yielded the best model performance.

4.2 Model Performance

The performance of trained models was evaluated using three metrics—Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Symmetric Mean Absolute Percentage Error (SMAPE). RMSE measures the square root of the average of squared differences between predicted and observed values, providing insight into the model's accuracy. MAE, on the other hand, measures the average of the absolute differences between predicted and observed values, offering a straightforward interpretation of prediction error. SMAPE, a percentage-based metric, assesses the accuracy of predictions by comparing the absolute difference between predicted and observed values relative to their average.

Figure 3 summarizes the performance of various models in predicting operating speeds, both with and without the speed limit feature. Linear regression models in both cases exhibited relatively high error metrics, indicating inferior performance. Random forest had much better

performance compared to linear regression, highlighting the effectiveness of ensemble methods in handling complex data structures. XGBoost achieved the best results among the models tested, with the lowest RMSE, MAE, and SMAPE both for models with and without speed limits, demonstrating its robustness and efficiency in predicting operating speeds. The MLP Neural Network performed better than linear regression but did not match the performance of Random Forest and XGBoost models.

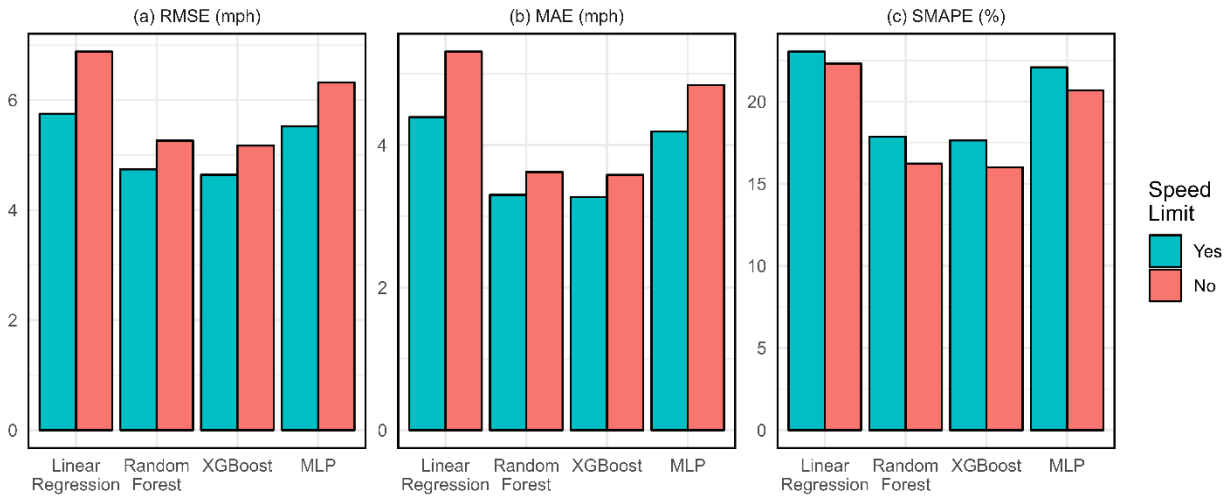


Figure 3: Performance of machine learning models in predicting operating speeds.

Comparing models with and without the speed limit feature, all models without this feature showed a decline in performance, emphasizing its importance in speed predictions. This observation is consistent with findings in Himes and Donnell (2010). Linear regression models exhibited the most significant drop in accuracy, underscoring their reliance on the speed limit feature. Random forest and XGBoost performed relatively well even when the speed limit feature was taken out, owing to their capability to manage non-linear interactions. The MLP model also saw a noticeable decrease in performance. It is worth noting here that the performance of XGBoost is only slightly better than random forest. Hence using either of these models for predicting operating speeds would work just fine.

(a) Model with Speed Limit **(b) Model without Speed Limit**

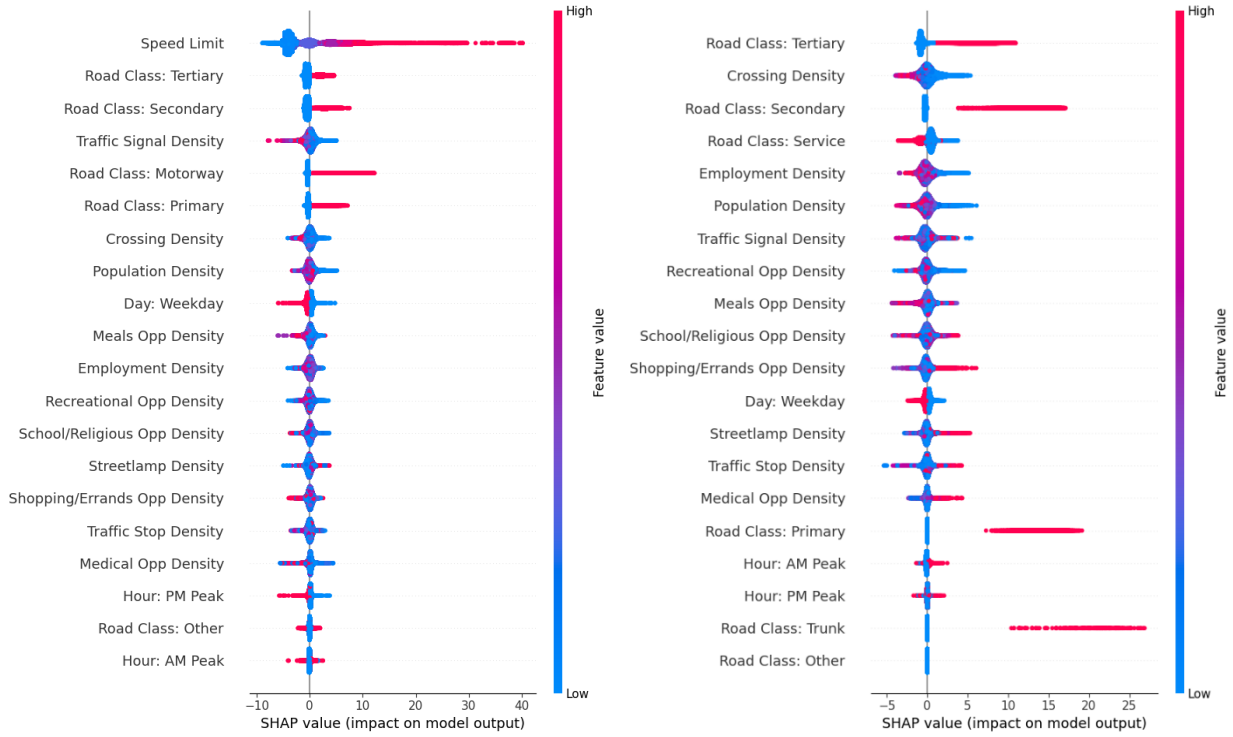


Figure 4: SHAP distribution of features in operating speed prediction models with (a) and without (b) speed limit as a features.

Relative importance of various features used for model estimation was interpreted using the SHapely Additive exPlanations (SHAP values) (Lundberg & Lee, 2017). The dominance of the speed limit feature, conjectured from the results in **Table 2** can be corroborated by the SHAP values presented in **Figure 4**(a). Speed limit appears to exert a positive influence on predicted speed. In other words, the higher the speed limit, the higher the operating speed on a link, which is intuitive. Road class also has a marked influence on predicting operating speeds. SHAP values indicate that a higher traffic signal density will lead to a lower predicted speed, consistent with expectation. When the speed limit feature was absent, other features such as crossing density and as well as population and employment density stepped into the role of predicting speeds on the network (i.e., have higher SHAP values). Features such as streetlamp density and traffic stop density had relatively lower importance in both models. Interestingly, the opportunity variables exert relatively minor influence on speed predictions. The combination of two XGBoost models was applied to predict operating speeds for the six day-hour pairs for all the 434,959 links in the Denver metro region.

Table 2 presents a summary of mean percentage differences in observed vs. predicted operating speeds for different day-hour pairs and for different road classes. A few interesting insights can be drawn from this table. Firstly, motorways have the lowest mean percentage difference between observed and predicted speeds (15.5% - 20.2%) while service roads have the highest percent difference (36.6% - 40.1%). There could be a couple of reasons for this. First,

motorways have 0% of the links with missing speed limit information while 98% of the service roads do not have speed limit information. Given the importance of speed limit in predicting operating speeds (as shown in Figure 3), it is intuitive that model predictions for services roads that lack this information are inferior. Second, the speeds on motorways (aka freeways) are much higher compared to service roads. So, getting a prediction off by 5 mph on a freeway will show a much smaller percent impact compared to getting it wrong by the same 5 mph on service road with a much smaller speed limit. While evening periods have the lowest prediction accuracy on weekdays, the performance of the model is about the same during all periods on a weekend. Further exploration is required to decipher the reason for the model's inferior performance in predicting weekday evening speeds.

Table 2: Operating speed prediction accuracy across different road class and time periods. The values indicate mean percentage differences in predicted speeds compared to observed speeds.

Road Class	Weekday Morning	Weekday Afternoon	Weekday Evening	Weekend Morning	Weekend Afternoon	Weekend Evening
Motorway	17.3%	15.5%	20.8%	16.0%	16.0%	16.6%
Trunk	19.6%	19.6%	19.5%	20.4%	19.7%	19.3%
Primary	19.0%	19.2%	21.5%	20.3%	21.1%	22.7%
Secondary	17.2%	17.3%	19.8%	17.4%	18.8%	19.0%
Tertiary	20.1%	19.9%	21.5%	20.6%	21.1%	21.7%
Residential	21.9%	21.6%	21.3%	23.4%	21.8%	21.6%
Service	38.7%	38.3%	35.8%	40.1%	37.7%	36.6%
Other	22.3%	21.8%	23.4%	24.2%	23.3%	23.5%

5. Accessibility Calculation Using the Mobility Energy Productivity (MEP) Metric

5.1 MEP Metric and Data Sources

The impact of operating speed variations is demonstrated using accessibility calculations. While many accessibility metrics account only for time decay in accessing opportunities (e.g., Actionfigure, 2024; Lee & Holme, 2015), the Mobility Energy Productivity (MEP), developed by the National Renewable Energy Laboratory (NREL) accounts for multiple dimensions including time, energy and cost when computing accessibility scores (Hou et al., 2019). Building on existing accessibility metrics, MEP presents a way to incorporate access to various types of opportunities into a single measure. Put simply, the MEP metric evaluates how effectively and efficiently transportation systems facilitate access to jobs and amenities, such as restaurants, grocery stores, educational facilities, recreational opportunities, and hospitals. In this study, accessibility to various opportunities is computed using this multi-modal, multi-activity, and multi-dimensional MEP metric. Higher MEP scores in a region indicate a better quality of access and a more efficient transportation system. Although the metric can be used to assess the quality of connectivity provided by any mode, this study specifically focuses on accessibility for driving, since this is the mode that is most impacted by congestion.

The calculation of the MEP metric requires several data sources, including road networks, land use, and employment within the study region. Fortunately, all these data were readily available as they were processed for operating speed prediction model estimation

(presented in the previous section). The network topology was derived from OSM. The link level data was enriched with operating speeds predicted by the model for different day-hour pairs. Land use data were obtained from OSM's point of interest (POI) data and classified into five categories: school/religious, medical, shopping/errands, recreational, and meals. Job and employment data was extracted from US census sources.

For the purposes of this analysis, MEP scores can be interpreted as regular accessibility scores for a location; the higher the score, the better the accessibility. The MEP scores were computed at a 1 km^2 pixel resolution within the Denver metro area boundary and then aggregated to the city level using population weighting for the study region. There are several steps to calculate a MEP score for a location. First, isochrones are generated from a specified origin location using a minimum spanning tree approach (Nešetřil et al., 2001) for given travel time thresholds. Any arbitrary travel time thresholds can be considered for MEP calculation, but this study used thresholds of 10, 20, 30, and 40 minutes. Second, isochrones are intersected with the land use layer to quantify the raw number of opportunities (by activity type and including jobs) reachable within each travel time threshold. These raw opportunity counts are then normalized as O_{it} (where i and t are location and travel time threshold, respectively) for driving using

$$O_{it} = \sum_j O_{ijt} \left(\frac{N^*}{N_j}\right)\left(\frac{f_j}{\sum_j f_j}\right) \quad (1)$$

In this equation, N^* represents the number of benchmark opportunities (meals in this study), while N_j denotes the number of opportunities of activity type j. This normalization accounts for differences in the relative availability of various types of opportunities. To further normalize for varying levels of engagements among travelers in different types of opportunities, the frequency of engagement for opportunity type j (f_j) is aggregated across all opportunity types. Finally, the normalized opportunity counts are discounted based on the time, cost, and energy required to reach them, resulting in a final MEP score for driving using

$$M_{it} = \alpha e + \beta t + \sigma c \quad (2)$$

$$MEP_i = \sum_t \left(O_{it} - O_{i(t-10)}\right) e^{M_{it}} \quad (3)$$

In (2), M_{it} is the modal weighting factor, e is the energy intensity of driving (in kWh/PMT), t is travel time (in min), c is the cost of driving ($/PMT). This study used default weights for energy, time, and cost established in Hou et al. (2019) ($\alpha = \sigma = -0.5$; $\beta = -0.08$). More details on the MEP methodology can be found in Hou et al. (2019), and a detailed example MEP calculation is described for a location in Denver in Hoehne et al. (2024).

5.2 MEP Scores for Various Hours and Days

Out of 434,959 links within the Denver metro region, 353,210 (81% of links count) had missing speed limits. The best performing models (i.e., XGBoost) were applied to the OSM network for datasets with and without speed limits, resulting in a final network with predicted

speeds for different day-hour pairs. Six different operating speeds were predicted for each network link: weekday morning, weekday afternoon, weekday evening, weekend morning, weekend afternoon, and weekend evening.

Calculations based on free flow speeds can serve as a benchmark to demonstrate the impact of congestion on accessibility. Since free flow speeds were not readily available, OSM speed limits were used as a proxy, where available. For 81% of the road links with missing speed limits, free flow speeds were imputed using the median speed limit specific to each road class based on data from links with speed limit information. Seven different speeds (free flow + six day-hour pairs) were used to compute MEP scores, holding all other inputs (network topology, land use opportunities, population, and job data) constant. In parallel, seven additional MEP calculations were carried out using observed operating speeds from the commercial vendor. 85th percentile weekday afternoon speeds serve as free flow speeds (i.e., benchmark) for proprietary data. **Table 3** presents a summary of the MEP results.

Table 3: MEP Scores for the Denver metro region across different hours and days computed using OSM model-predicted and proprietary observed speeds.

Operating Speed Type	OSM model-predicted		Observed	
	MEP	% drop in MEP[b]	MEP	% drop in MEP[b]
Free flow[a]	220		254	
Weekday morning	157	29%	166	35%
Weekday afternoon	173	21%	194	24%
Weekday evening	127	42%	142	44%
Weekend morning	189	14%	218	14%
Weekend afternoon	180	18%	208	18%
Weekend evening	171	22%	202	20%

[a]Speed limits and 85th percentile weekday afternoon speeds serve as free flow speeds for OSM and the commercial vendor, respectively.

[b]The percentage drop in MEP scores for different hours and days compared to free flow speeds.

The comparison of city-wide MEP scores across these datasets reveals that MEP scores computed using the model-predicted speeds are slightly lower than those observed from the proprietary data across all hours and days. This is to be expected as the performance of any model falls short of replicating ground truth, and the speed prediction model presented in this paper is no different (as observed from **Table 3**). However, it is encouraging to see that the percentage drop in MEP scores remains consistent between OSM model-predicted and observed speed data from commercial vendor for different day-hour pairs. For instance, during the most congested hour—weekday evening—OSM model-predicted operating speeds lead to a drop in MEP scores by 42%, compared to the third-party's 44% reduction. The least drop in MEP scores (or accessibility) of 14% was observed from both data sources during weekend mornings.

Figure 5 presents a comparison of square kilometer pixel-level MEP scores based on predicted vs. observed operating speeds for weekday morning, afternoon, and evening. This comparison demonstrates a strong correlation (greater than 0.98 and statistically significant) between OSM model-predicted and third-party observed operating speeds for all time periods.

These findings collectively suggest that OSM model-predicted speeds effectively capture the impact of congestion on accessibility, and the magnitude of these impacts is similar to that of observed speeds giving confidence that the model-predicted speeds can be used to compute accessibility scores such as MEP.

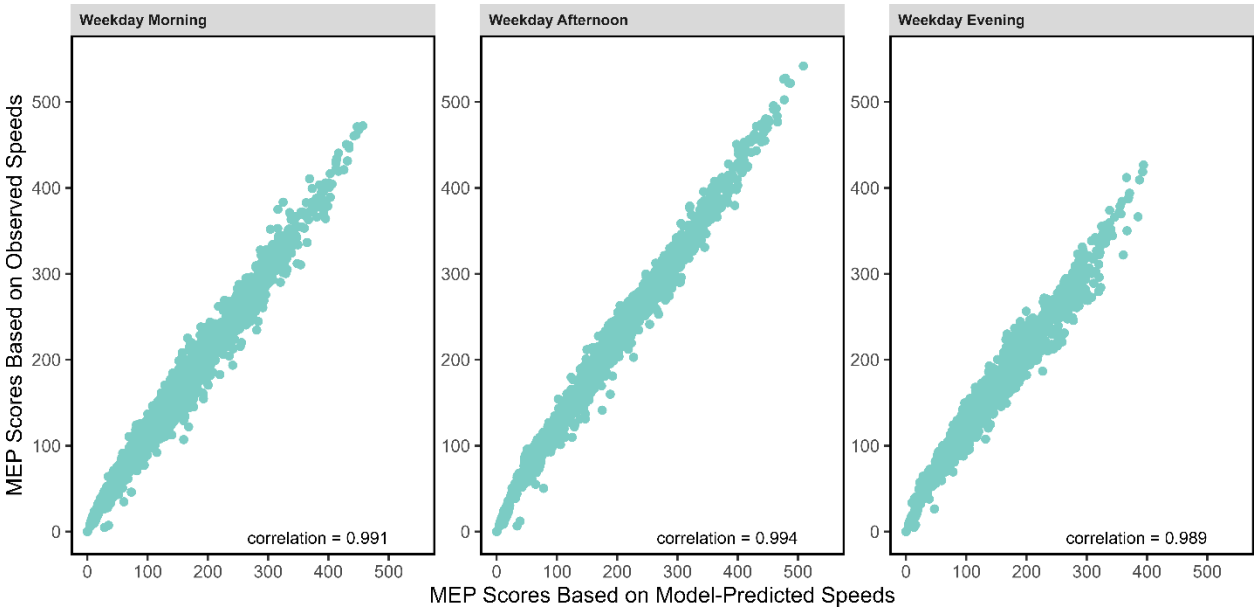


Figure 5: Comparison of pixel-level MEP scores calculated using model-predicted (OSM) and observed (proprietary) operating speeds across various weekday hours.

5.3 Insights from Access Calculation for the Study Region

The free flow speed-based MEP calculation using OSM network (from **Table 3**) resulted in a MEP score of 220 for the Denver metro region. Across all six time periods analyzed, the MEP scores were consistently lower than the free flow speed-based MEP scores (also considered as baseline scores). Weekday evenings exhibited the largest drop (~42%) in overall MEP score compared to free flow speed-based MEP. Similarly, weekday mornings and afternoons experienced drops of 29% and 21%, respectively. Weekends demonstrated higher overall accessibility compared to weekdays, as expected, but still fell short of free flow conditions accessibility.

The MEP metric also allows for analyzing the accessibility of various types of opportunities. Using the MEP framework, population-weighted average number of opportunities were computed for different activity types within different travel time thresholds using both free flow speeds and operating speeds during different hours and days of the week. **Figure 6**(a) presents the average number of medical opportunities and jobs accessible within different travel time thresholds when using free flow speeds, while **Figure 6**(b) and (c) depict the decline in average number of accessible opportunities during weekday morning and evening hours in the Denver metro region. On average, 100 medical facilities and 20,000 jobs are accessible within a 40-minute travel time using free flow speeds. However, during weekday morning and evening hours, accessibility to medical opportunities drops by 40% and 52% in the 10-minute threshold, and by 20% and 35% in the 40-minute threshold, respectively. Similarly, job accessibility

decreases by 52% and 30% during weekday evening hours for the 10- and 40-minute thresholds, respectively, consistent with the observations of Owen and Murphy (2019). These findings underscore significant variations in overall accessibility and access to different types of opportunities across different times of day, which do not always align with free flow speed-based calculations.

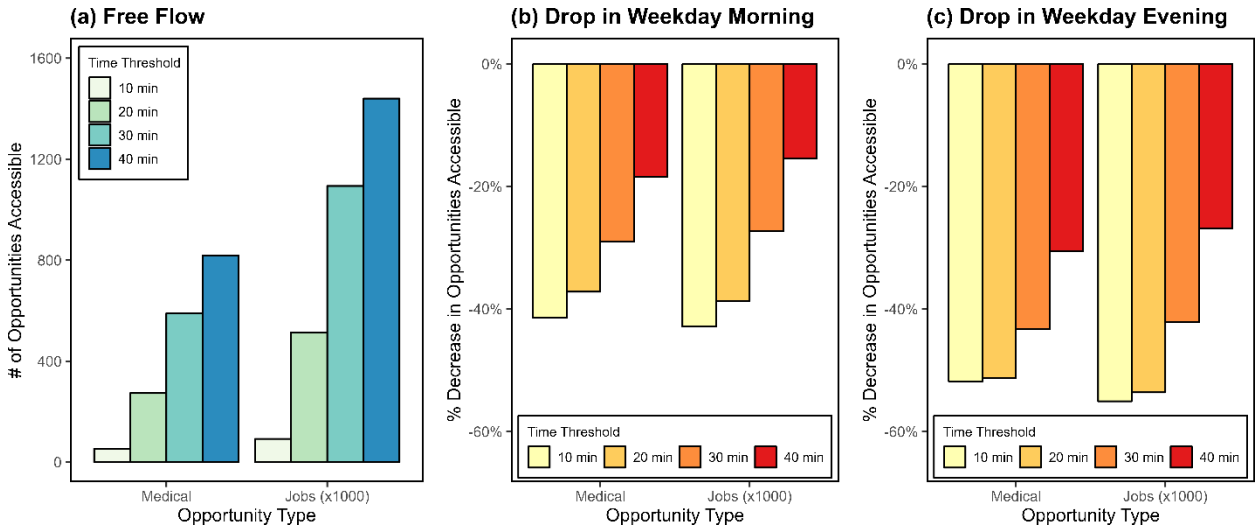


Figure 6: Average opportunities accessible in free flow conditions (a) and drops in opportunities accessible during weekday morning (b) and evening (c) hours.

To assess the regions within the city with varying impacts of congestion on accessibility, pixel-level MEP scores across different hours and days were compared with the scores obtained using free flow speed. **Figure 7**(a) shows free flow speed-based MEP scores and the drop in scores during weekday morning and evening hours are presented in **Figure 7**(b), and (c) respectively. From the figures, it can be observed that the areas around downtown are the most impacted by congestion, which is consistent with expectation. The triangle of congestion formed by I-25, I-70, and I-225 is revealed through a significant drop in MEP scores, which is particularly evident in **Figure 7**(c), indicating that the model is able to depict spatial congestion patterns in Denver quite accurately.

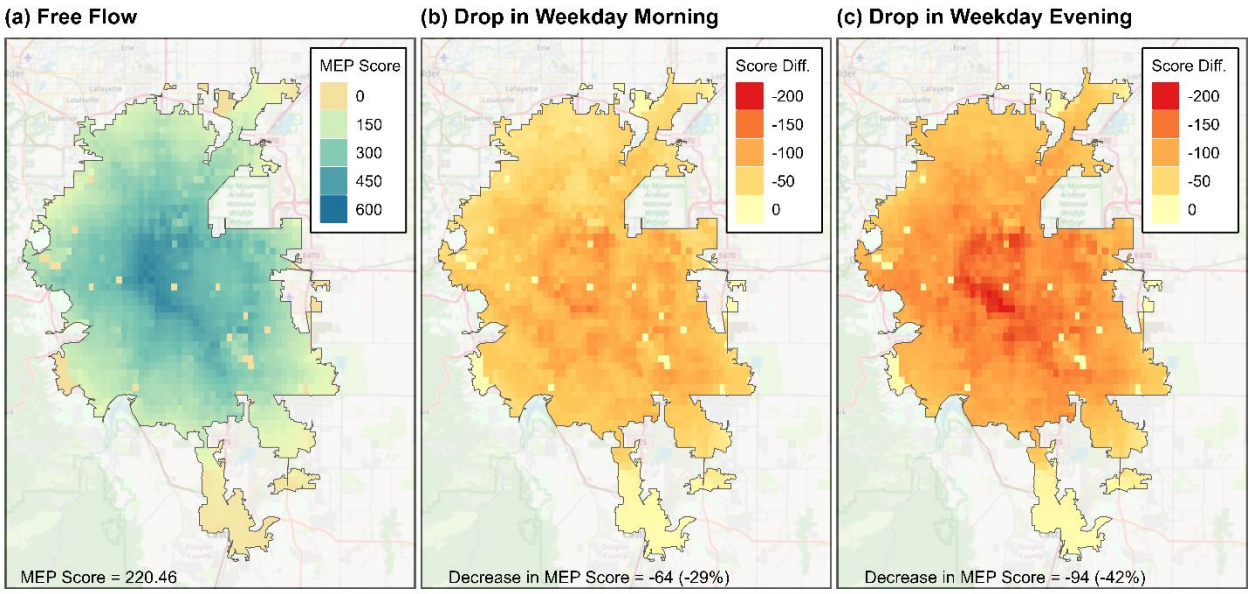


Figure 7: MEP scores for the Denver metro region using free flow speeds (a) and drops in MEP scores during weekday morning (b) and evening (c) hours.

6. Discussion

Access to open-source, and up-to-date network and land use information is critical for a variety of applications in transportation planning and operations. OpenStreetMap (OSM) addresses this need by providing a free crowdsourced map of the world. However, OSM networks lack information pertaining to operating speeds which is crucial for several transportation applications including but not limited to access calculations. This study bridges this gap by developing models to accurately predict operating traffic speeds for OSM links in the Denver metro region. The predicted speeds are utilized to demonstrate the impact of congestion in accessibility calculations using the Mobility Energy Productivity (MEP) metric.

6.1 Key Findings

The study leveraged transport infrastructure (road and traffic characteristics), land use, demographics, temporal features were leveraged to estimate a linear regression model, and three machine learning models—random forest, extreme gradient boosting (XGBoost), and multi-layer perceptron (MLP) neural network —to predict operating traffic speeds on OSM networks. Historical traffic speed data obtained from a commercial vendor was used as the ground truth to estimate speed prediction models. Separate models were estimated for OSM links with and without speed limits. Among the models estimated, random forest and XGBoost performed relatively well for both types of links, with XGBoost showing the best overall performance. It achieved RMSE, MAE, and SMAPE values of 4.64, 3.27, and 17.64%, respectively, for links with speed limits, and 5.17, 3.58, and 16.01% for links without speed limits. From the features selected for model estimation, speed limit (when available), road class, traffic signal density, as well as population and employment density appeared to have the greatest explanatory power in predicting operating traffic speeds. The predictive ability of the best performing model was corroborated through strong alignment with observed speed data.

To assess the impact of congestion on accessibility, the predicted speeds were used to compute accessibility scores in the study region utilizing the MEP metric. This allowed for the evaluation of accessibility metrics during different time periods, highlighting the temporal dynamics of congestion's impact on spatial accessibility. A comparison of accessibility calculations using free flow speeds and predicted traffic speeds at different times of days for the Denver metro area revealed that weekday evening peak periods showed the most significant drop in accessibility compared to free flow conditions. Conversely, weekend mornings and afternoons experienced the smallest reductions in accessibility relative to free flow conditions. Overall, the impact of congestion on driving accessibility was considerable with approximately half as many opportunities and jobs are accessible within 20 minutes by car during evening peak periods compared to free flow conditions. The use of predicted speeds to estimate accessibility in OSM networks demonstrated similar patterns of accessibility by time of day and opportunity type as observed speed data. This validation underscores the robustness of the estimated model, and as well as the impact of traffic speeds on accessibility loss.

6.2 Limitations and Future Work

This study presents a robust methodology for enriching OSM networks with operating traffic speed data for different days and times. Nonetheless, several limitations remain. First, the study relies on availability of proprietary data as the ground truth. If such information was easily available or affordable, what benefit would come from enhancing OSM networks using congestion-adjusted operating speeds? The answer for this limitation lies in scaling the model to the national level by developing models for 'representative cities' across the country. A national level representation of operating traffic speeds on OSM networks could become a valuable proxy for researchers, practitioners, and policy makers alike.

Second, the models were trained in the Denver metro region, and their transferability to other regions has not been investigated. Future work should focus on testing this approach's transferability to other regions. We plan to calibrate the models using data from several additional cities with varying traffic characteristics, demographics, and urban morphology. These models could also benefit from incorporating city-level variables such as population, employment, urban morphology characteristics, and traffic congestion indicators (when available) to enhance their spatial transferability (Kasundra et al., 2022).

Third, the methodology used to join the OSM network with the proprietary network for calculating observed speeds on OSM links may introduce some errors, particularly when there are significant spatial discrepancies between links in the two data sources. While the use of weighted averaging by length reduced these errors to some extent, adopting more robust methodologies is recommended for future work. Additionally, it would be beneficial to generalize the approach presented in this paper to predict traffic speeds (or more broadly transfer network states) from any data source on to OSM networks. This can help facilitate transferring current as well as future network states simulated in travel demand models on to open-source networks such as OSM.

Finally, the accessibility scores, can also decrease because of reduced energy efficiency resulting from congestion, which was not accounted for in the current MEP calculations.

Integrating link-level energy estimation, which varies across different operating speeds, would help further refine the true impact of congestion on accessibility.

6.3 Implications

The accurate operating speed prediction models presented in this study can serve as an invaluable tool for urban planners and policymakers, offering reliable, data-driven insights into congestion patterns across different times of day and specific locations. These models enable a more strategic approach to urban planning, allowing cities to leverage congestion-adjusted speed data to optimize public transit schedules, prioritize road maintenance efforts, and make informed infrastructure investments that align with real-time needs. Furthermore, appending congestion-adjusted operating speeds to OpenStreetMap (OSM) networks broadens the utility of this open-source dataset across numerous applications. This enriched dataset can support advanced transportation modeling, enhance accessibility analyses, and provide a foundation for developing smarter urban policies.

With a deeper understanding of the temporal dynamics of congestion, cities can implement policies to alleviate peak-hour congestion, such as congestion pricing, staggered work hours, or improved public transportation options. Identifying locations where congestion most heavily impacts accessibility, as presented in Section 5.3, can help prioritize targeted interventions for congestion relief in specific areas, ultimately enhancing overall mobility and accessibility. The insights from this study could guide investments in high-impact areas, fostering equitable and efficient access to essential services, job centers, and opportunities. Ultimately, the implications of this research extend well beyond accessibility calculations, creating a path for data-driven policies that enhance urban quality of life, reduce traffic congestion, and contribute to sustainable urban development.

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