Comparing Automobile and Transit Travel Costs using a GIS Server Extension: A First Step Toward Ending Automobile Dependency

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ABBREVIATIONS

API	Application Program Interface
MWAAS	Middleware-as-a-service
MWCOG	Metropolitan Washington Council of Governments
NCRTPB	National Capital Region Transportation Planning Board
NCHRP	National Cooperative Highway Research Program
REST	Representational State Transfer
SOE	Server Object Extension
TAZ	Traffic Analysis Zone

There is a fundamental realization to consider in the way that an individual views the impact of their daily commute in terms of cost, and not just monetary. This project aims to provide a critical path toward breaking the general public's pervasive dependency upon automobiles. It is widely accepted that automobile transportation produces harmful greenhouse gases that contribute to air pollution, global warming, and climate change, as well as respiratory ailments (Centers for Disease Control and Prevention 2022). Automobiles are by far the largest category of emitters within the transportation sector, which in total accounted for 27% of all greenhouse emissions in the United States, from year 2019 to 2020 (EPA 2020). Yet the trends in automobile-driven fossil fuel consumption continue to increase each year (Energy Information Administration 2007). For the individual driver and health impacts, inactivity in conjunction with long commutes increases the rate of cardiovascular illness and obesity, two of the leading causes of death in the US (Hoehner et al. 2012). Additionally, before the onset of the COVID-19 pandemic in the US, fatal automobile accidents were listed among the top three leading causes of death (Centers for Disease Control and Prevention 2021). Socioeconomic research finds other deleterious issues linking automobile dependency to the lack of municipal tax revenue, wasted federal subsidies (Calthorpe 1993, Hanson 1995), ageing infrastructure (Duany and Plater-Zyberk 1992), inner-city crime (Kushner 2005), job loss (Kuby, Barranda, and Upchurch 2004), classism and even racism (Hanson 2001). Despite some level of public awareness about these costly outcomes, on any given day most commuters in the US are not likely to be dissuaded from driving. Most research literature on aggregate travel behavior and the built environment indicates that a dense, mixed-use, and transit-friendly settlement pattern does generate lower automobile miles travelled than a traditional suburban development. However, a substantial portion of this research also shows that any shift away from this ideal neo-urbanist community to broader urbanized areas exhibits only marginal – if any – influence upon travel behavior where changes to the built environment are involved. Moreover, the commuter who must traverse complex urban landscapes lacks information about the daily end-to-end costs associated with each mode of travel for their specific commuting pattern.

INTRODUCTION

In this project, the author theorizes a corollary link between travel behavior and the lack of information travelers have about "perceived" out-of-pocket costs, in terms of time and money, for each practical and available mode of travel. To begin exploration of this theory the author has created a two-tier GIS web application, called *Commute GeoCalculator*, that models the optimal cost paths for driving versus transit in minutes and dollars for commutes in central metropolitan Washington D.C (Pedigo 2023). The application is composed of a data tier (Tier 1) which constructs a routable, multimodal travel cost database from diverse source data, and a logic tier (Tier 2) as an Esri server object extension (SOE) that routes, reads, and computes travel costs over user-defined traversals on Tier 1. Based on the time of day, coordinates for origin and destination (OD), open source and proprietary data, authoritative input parameters, and the economic principle of utility (Case and Fair 2004), the SOE translates time, distance, and traveler income into dollar amounts for walking, waiting, transferring, driving, parking, and riding transit. Fuel cost per mile, parking fees, and transit fares are added where applicable. This two-tier web GIS sets up a comparison of optimal cost paths by travel mode over an unlimited number of trips, and serves as a starting point for acquiring a comprehensive understanding of travel behavior. In the next project phase, a third-tier mapping frontend will use *Commute GeoCalculator* services to assist individuals in their decision-making process regarding OD travel options. In this future release, the spatially translated costs will be computed and visualized simultaneously for users, who may then provide anonymous mode-choice feedback. Specifically, users shall be asked which mode will be chosen for their commute, and why it was chosen. Figure 1 shows the combined “as is” and future states of the project’s infrastructure, representing a mode-choice volunteered geographic information (VGI) system.

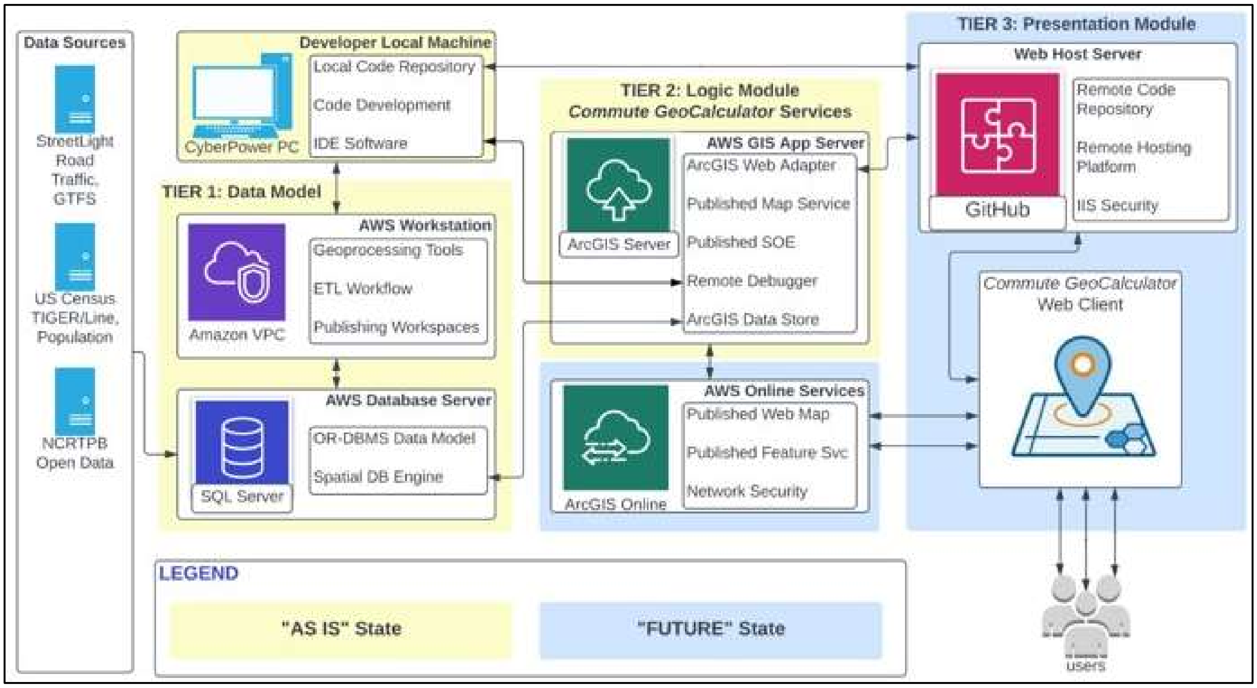

Figure 1. *Commute GeoCalculator* Infrastructure Diagram

PROJECT MOTIVATION: MODE CHOICE

Mode choice is an aspect of travel demand analysis that determines the number or percentages of trips between zones that are made by automobile and by transit. Whether one travel mode is preferred to another depends on how much utility, or satisfaction, it yields relative to its alternatives (Case and Fair 2004). Economic feasibility based on out-of-pocket costs, itself, may very well not be enough to guide the probable mode choice of most commuters in any given urban setting. However, it can be reasonably expected that most people who frequently commute would consider the economic feasibility of alternatives as a decision-making factor, along with efficiency, comfort, sense of security, safety, and environmental stewardship. All of which are target factors for the three-tier application to capture along with the associated path geometries for every single commute. Shunk and Bouchard (1970) point to the development of an independent decision variable based upon marginal “disutilities” (dissatisfactions) of travel by competing modes as perceived by a traveler. Their study shows how a model that is basically more behavioristic in nature rather than simulative conceivably could lead to more effective modal-choice prediction procedures. Particularly where changes to the built environment promote the use of transit, empirical mode-choice data present an opportunity toward improving studies of travel behavior (Pieri and Nelson 1999).

ESRI APPLICATION DEVELOPMENT AND RESULTS

A complete listing of project resources is provided in Table 1. A specific temporal scale is applied to the source data in Tier 1. Fully processed traffic volumes and household income are averaged on weekends and weekday peak/non-peak times for 2019. Specifically, trip speed and traveler annual income are provisioned by StreetLight Data, Inc. (SL) in US-standard traffic analysis zones (TAZ). The parking penalty values (Table 2.) depend on the population density in each census block group multiplied by the percentage of employed in the civilian labor force (Table 3.). Spatial source data are updated in a local file geodatabase while non-spatial data are setup in a "staging" remote database – all of which undergo a remove-and-replace manual procedure. However, once all source data are loaded, ETL automation developed as part of this project handles all data crunching. The *commuters* data model, shown in its separate database of Figure 2, is planned for future development to store users' mode choice responses to the dynamic commuting cost returns.

Table 1. Project Source Content

Source/Dataset	Organization	Coefficient Weights	Trip Variables	Analysis Layers
MWCOG / NCRTPB Model	MWCOG / NCRTPB	●		
NCHRP Report 716 – Model D	Transportation Research Board	●		
2020 Pct Employment	U.S. Census Bureau	●		
2020 Population Density	U.S. Census Bureau	●		
2019 GTFS Calibration Data	OpenMobility Data		●	
2019 Transit Service Indexes	StreetLight Data, Inc.		●	
2019 Road Trip Volumes.	StreetLight Data, Inc.		●	
Traffic Analysis Zones	StreetLight Data, Inc.		●	
2019 TIGER/Line Road and Rail	U.S. Census Bureau			●
2022 Metro Rail Lines	NCRTPB Data Clearinghouse			●
2022 Metro Rail Stations	NCRTPB Data Clearinghouse			●
2022 Metro Bus Stops	NCRTPB Data Clearinghouse			●
2019 Metro Bus Lines	NCRTPB Data Clearinghouse			●
2022 Pedestrian Trail Network	NCRTPB Data Clearinghouse			●
ArcGIS Network Analyst	Esri			●

Table 2. Parking Penalty Time (NCRTPB 2020)

Employment Density Range (Emp/Block Group)	Parking Penalty (Minutes)
0 - 4,617	1
4,618 - 6,631	2
6,632 - 11,562	4
11,563 - 32,985	6
32,986 +	8

Table 3. Percentage of the Civilian Labor Force Employed in MWCOG (US Census 2020)

County or District	Percent Civilian Labor Force in Population (2020)
Arlington County	77.00%
District of Columbia, Washington	70.20%
Fairfax County	70.20%
Prince George's County	70.90%
Montgomery County	70.50%

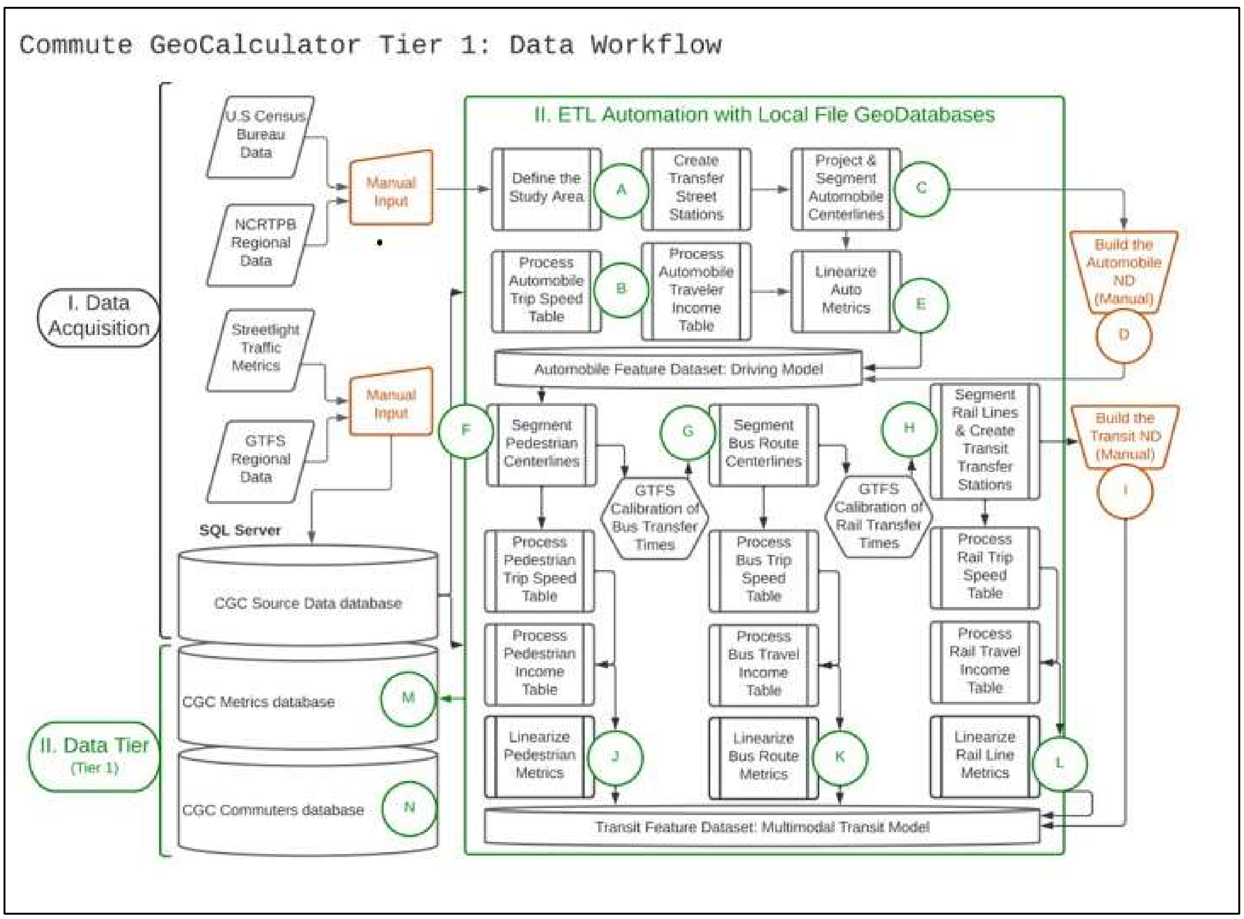

Figure 2. Tier 1 Workflow

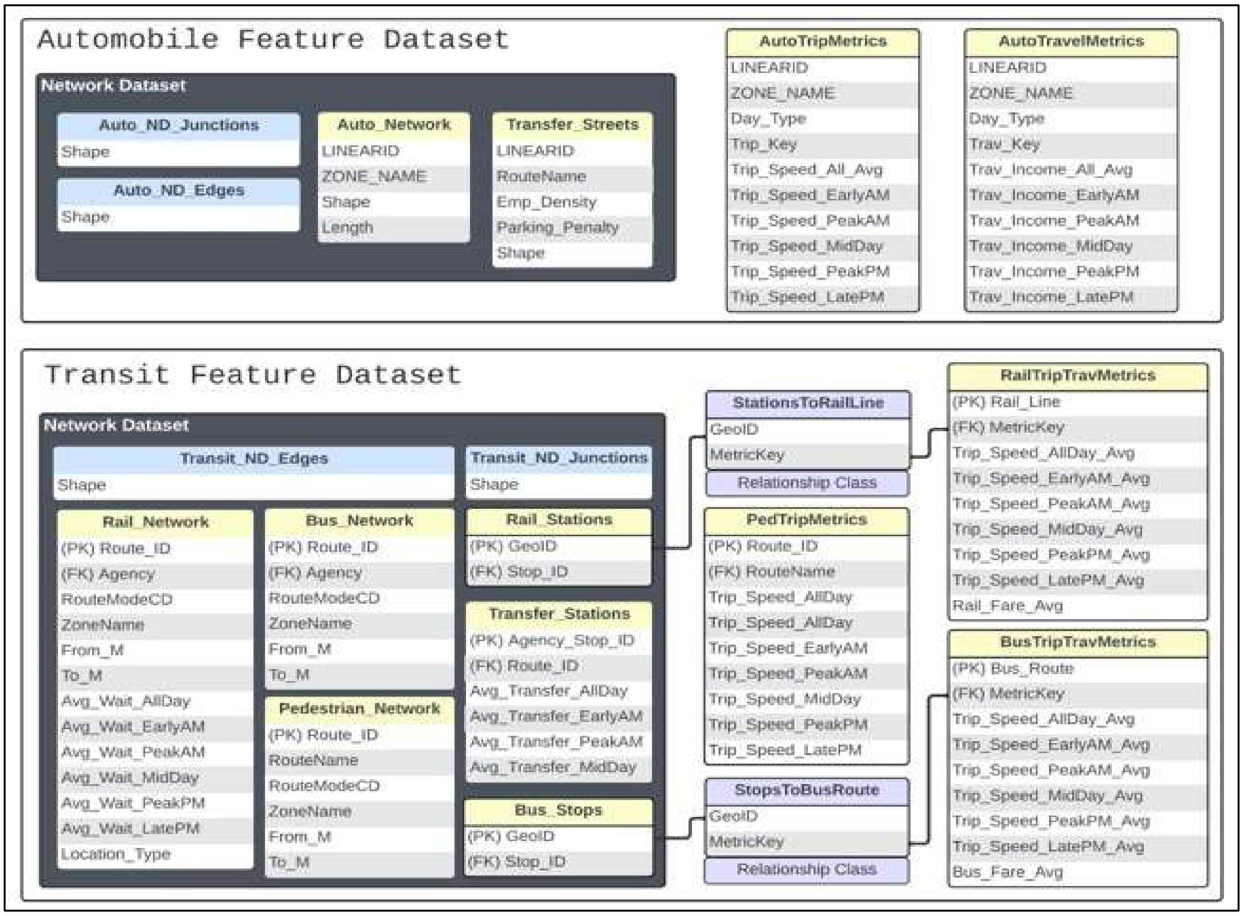

Figure 3. Tier 1: MS SQL Server *Metrics* Data Model

The *metrics* data model represents the cost data of each travel mode, composed of automobile and transit feature datasets. In the "static" database, the *metrics* data model includes two relationship classes linking transit stops to the route segments they service, for bus and rail modes. This allows the SOE to quickly locate intermodal transfers and the associated costs, without necessarily incurring the extra runtime needed for a database query (Butler 2008). The geographical data that are pertinent to the shortest-cost path are applied in the construction of each network dataset, and the metrics associated with the subsequent traversal costs are installed outside of the network dataset. A cross-sectional view of all base metrics on one roadway segment is depicted in Table 4. Data sources and source formats are indicated in the column headers at the top of this table, while the rows present precisely how each attribute is organized on the project's temporal scale. The column footers at the bottom of Table 4 convey which attributes are assigned as costs for determining path routing within Esri network datasets (Esri 2019), and which attributes are path-dependent metrics assigned to variables after routing.

Table 4. Tier 1 Sample Data: Cross-Sectional View

<table>
<tr><td colspan="3">US Standard Traffic Analysis Zones</td><td>US Census Streets</td><td>Bus and Rail Stops</td></tr>
<tr><td rowspan="10">Day Type:
1. Weekday
2. Weekend

Day Part:
0. All Day
1. Early AM
2. Peak AM
3. Mid-Day
4. Peak PM
5. Late PM

Data Period:
2019</td><td colspan="2">StreetLight Traffic and Traveller Metrics (GPS and LBS)</td><td>Employment Density</td><td>GTFS Calibration Data</td></tr>
<tr><td>AUTOS and TRANSIT</td><td>AUTOS and TRANSIT</td><td>AUTOS</td><td>TRANSIT</td></tr>
<tr><td>Trip Speed (mph)</td><td>Traveller Income ($)</td><td>Parking Penalty (mins)</td><td>Transfer Wait (mins)</td></tr>
<tr><td>19.3</td><td>90100</td><td>4</td><td>7</td></tr>
<tr><td>24.5</td><td>68000</td><td>2</td><td>0</td></tr>
<tr><td>14.2</td><td>118000</td><td>5</td><td>10</td></tr>
<tr><td>16.8</td><td>79000</td><td>7</td><td>15</td></tr>
<tr><td>12.5</td><td>113500</td><td>5</td><td>5</td></tr>
<tr><td>28.4</td><td>72000</td><td>1</td><td>5</td></tr>
<tr><td colspan="2">Applied to Centerlines</td><td colspan="2">Applied to Network Datasets</td></tr>
</table>

The source data used to build the project's data model were initially unusable for such an application (Pedigo 2023). Source travel speeds and traveler incomes were provided as percentages over a set interval of movements detected within each traffic analysis zone. For the project, this temporal range of values had to be dissolved and linearized into the average trip speeds and traveler incomes along facilities in each zone. The direction of travel was lost during this process. Hence, while the SL TAZ polygons do provide valid characteristic units of measurement, a low level of ecological fallacy resides in the current model. Future enhancement work will address this simplification in the data model, while preserving the full context of results using only input OD coordinates and the time of day, as defined in Table 5. Figures 4 - 6 demonstrate this capability from a sample commute scenario.

Table 5. Time of Day Input Parameter

Day Part Description	Weekday Entry Value	Weekend Entry Value
All-Day Average	1:AllDayAvg:Weekday	7:AllDayAvg:Weekend
Early AM (12am – 6am)	2:EarlyAM:Weekday	8:EarlyAM:Weekend
Peak AM (6am – 10am)	3:PeakAM:Weekday	9:PeakAM:Weekend
Mid-Day (10am – 3pm)	4:MidDay:Weekday	10:MidDay:Weekend
Peak PM (3pm – 7pm)	5:PeakPM:Weekday	11:PeakPM:Weekend
Late PM (7pm – 12am)	6:LatePM:Weekday	12:LatePM:Weekend

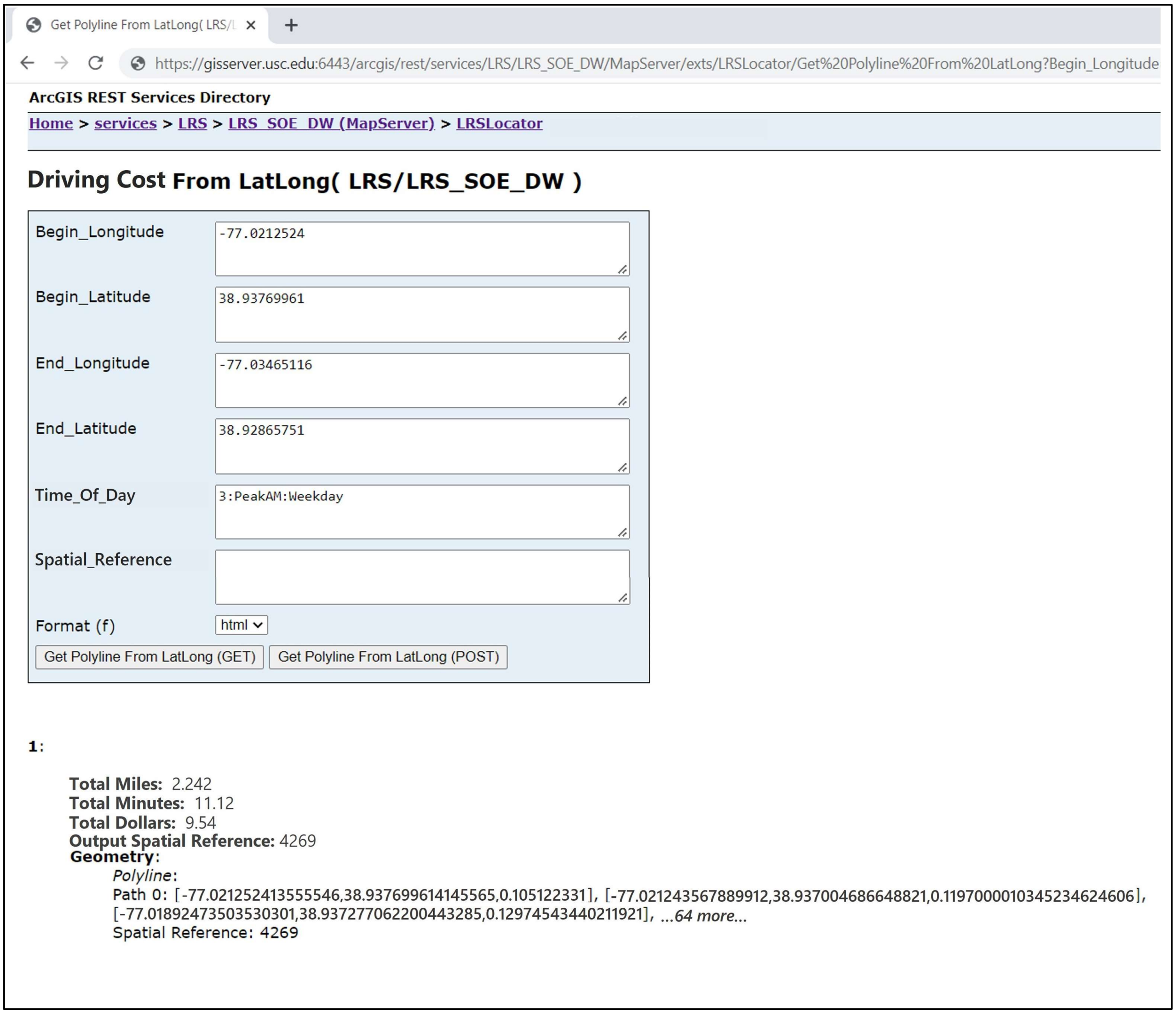

Figure 4. Trip Sample A - Automobile Travel Cost Return

To arrive at the shown cost totals, link mean speed, μS_L, is provided by day type (weekday or weekend) and day part (early AM, peak AM, mid-day, peak PM, and late PM). The total cost in minutes, T_A, is the sum of all link travel times along the routed path, plus parking penalties.

$$\text{Total Cost (in minutes), } T_A = \sum_{d=1}^{n} (D_L / \mu S_L)_d + KT \qquad (1)$$

where $(D_L / \mu S_L)_d$ is the link drive time composed of D_L, the link distance, and μS_L, the link mean speed. KT is equal to the parking penalty time, and n is the number of road links.

$$\text{Total Cost (in dollars), } C_A = (pVT \times T_A) + (pCM \times D_T) + KC \qquad (2)$$

where pVT represents the MWCOG value of time parameter; pCM is roadway fuel cost derived from the national-level model in NCHRP Report 716, plus inflation at $0.24 per mile; D_T is the total drive distance; and KC is given as the estimated parking fee, also according to MWCOG:

$$\text{Estimated Parking Fee, KC} = 2.1724 \times \ln(\text{employment density}) - 15.533 \qquad (3)$$

For this same trip sample, the multimodal transit costs in the REST page are depicted in Figure 5. Instead of segment endpoints connecting junctions between these networks by default, bus stops, transfer stops, and rail stations serve this purpose in the transit route analysis layer.

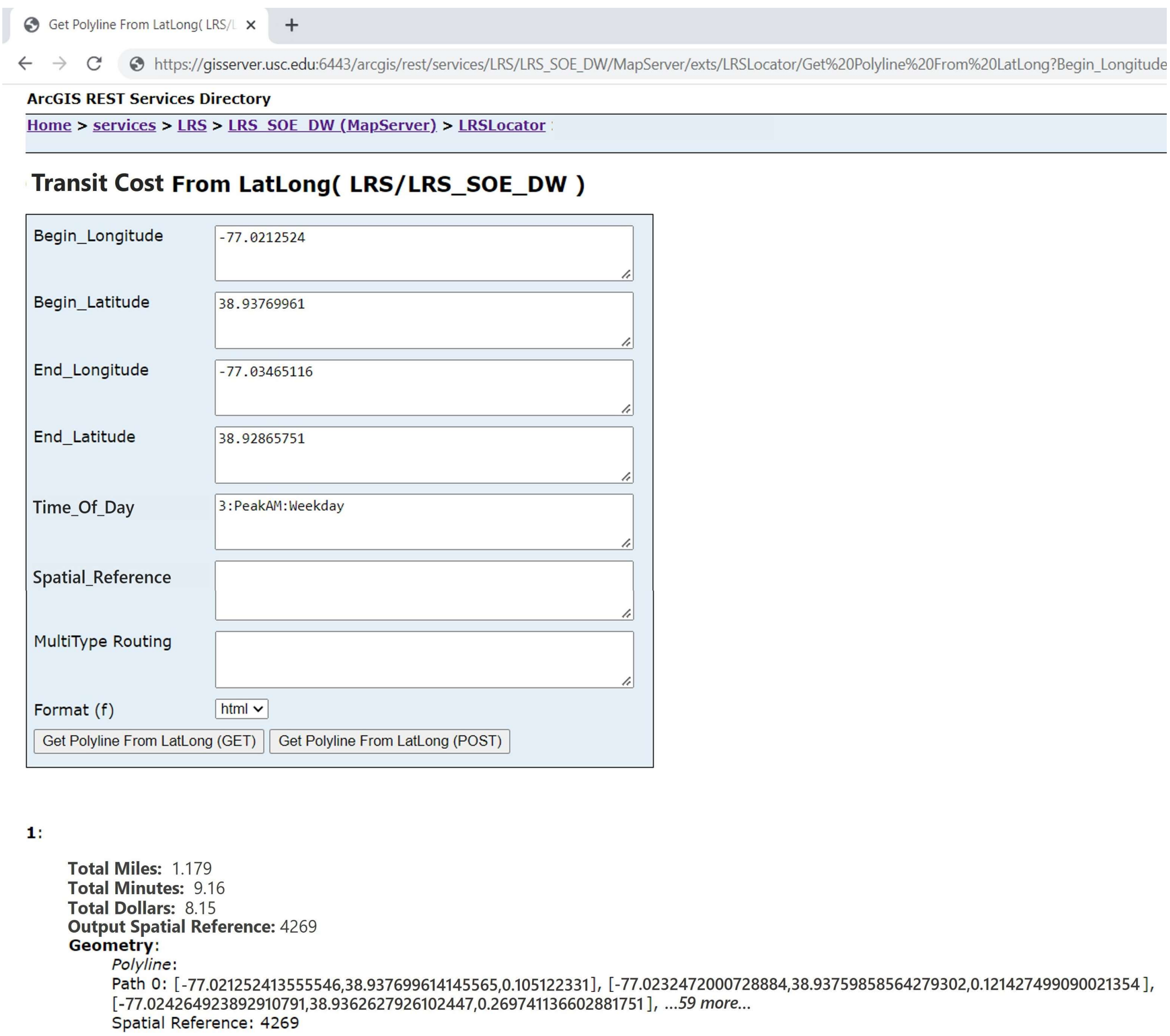

Figure 5. Trip Sample A – Multimodal Transit Travel Cost Return

Modal split is preconfigured in the elements of the transit network dataset for pedestrian, bus, and rail modes. The bicycle mode is planned for a future project phase. Using the solved path generated by Esri Network Analyst software, all trip speeds and traveler incomes are spatially extracted from each mode-specific centerline layer. For the pedestrian mode, the centerline layer consists of a pedestrian path layer that has been merged with local road links. For bus and rail modes, careful tracking of the service line within each respective centerline is required, from the first point of entry to the last. The cost equation set for transit is as follows:

$$\text{Total Cost (in minutes), } T_M = [\sum_{p=1}^{w} (P_L/\mu S_L)_p + \text{WaT}] + [\sum_{b=1}^{x} (B_L/\mu S_L)_b + \text{W2T}_b] \quad (4)$$

$$+ [\sum_{r=1}^{y} (R_L/\mu S_L)_r + \text{W2T}_r] + \text{Wa2T*}$$

where $(P_L/\mu S_L)_p$ is the link walk time; $(B_L/\mu S_L)_b$ is link bus time; $(R_L/\mu S_L)_r$ is link rail time. Here, each numerator and denominator replicates the quotient of link distance over mean speed used in the automobile cost equation. WaT represents the wait time, W2T_b the bus transfer time, W2T_r the rail transfer time, and Wa2T* the intermodal transfer wait time between bus and rail.

$$\text{Total Cost (in dollars), } C_M = [\text{pVT x } T_M] + (F + \text{F2T*}) \quad (5)$$

where pVT is the value of time parameter; F is equal to the fare cost of the initial bus or rail route, and F2T* is the fare cost of any ensuing transfer. Transit fares (F, F2T*) and intermodal transfer wait times (Wa2T*) between bus and rail are gathered and processed within separate server objects. Fare costs are applied to the linearized metrics based upon the average fares of each transit operator, and then exposed after network paths are solved. Tracking dynamic pricing for transit fares is planned as a future improvement. Finally, the sum of intermodal transfer times are added to the transit equation (4) for the time-based cost, just before it is solved. Once equation (4) is fully executed, then the sum all fares are added to the product of total time expenditure (T_M) and the value of time parameter (pVT) to solve equation (5).

Figure 6 shows the geometry paths for the commute sample submitted at each REST page in Figures 4 - 5. This particular case involves a transfer from rail to a bus route at a rail station well before the destination point, that is otherwise closer to a different rail station. Here, the path solution accepts a lower transfer time from the “BusToRailTransfer” value, relative to the

“RailToRailTransfer” value at “Rail Station 2”. This means that the bus transfer times along the remaining path to the destination are lower than the impedance measured from taking the route through “Rail Station 3”.

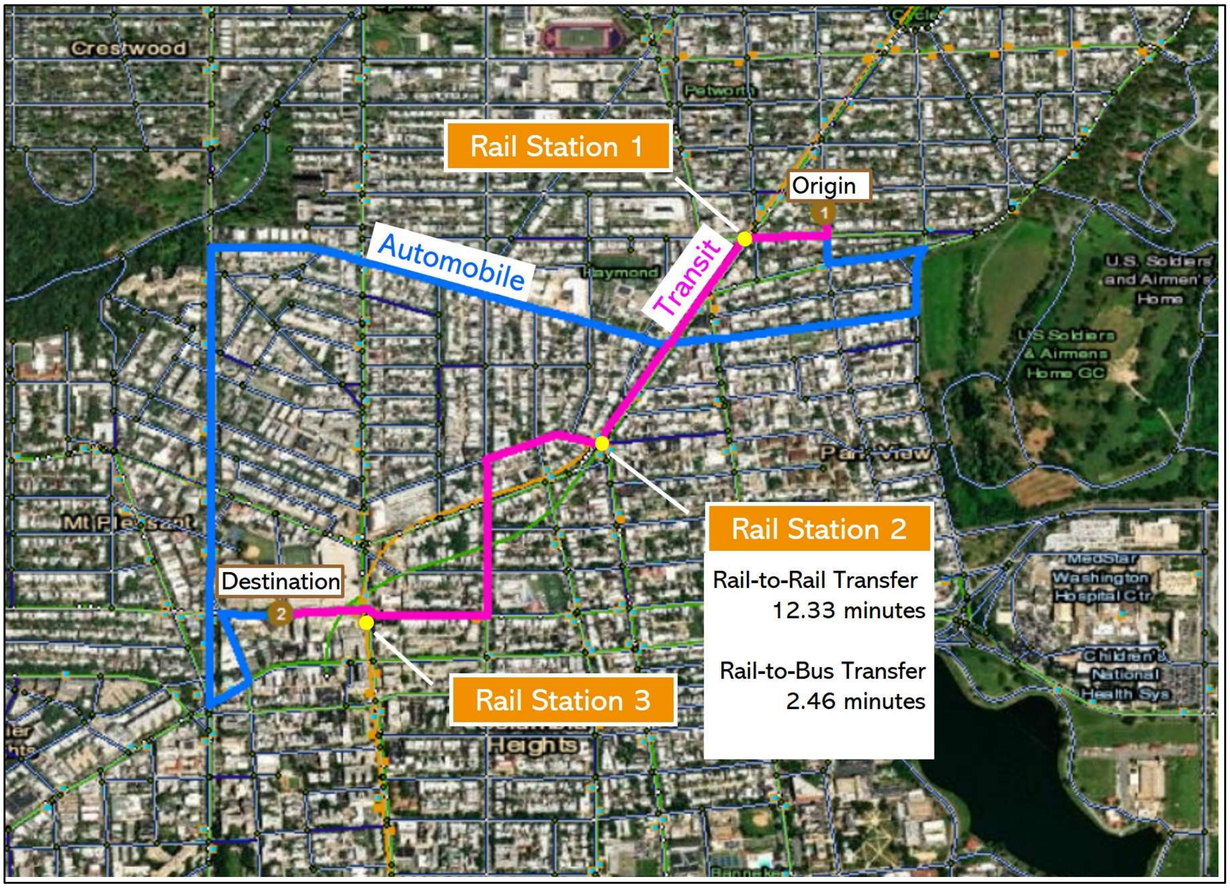

Figure 6. Trip Sample A – Transit and Automobile Outputs in ArcGIS Pro®

The very thin orange line shown in Figure 6 is the local rail line. By comparison, another noteworthy outcome in the above depicted sample is the path solved for automobile travel. Parking time (penalty) is applied to routing and longer parking times indicate higher employment density by census block group, which suggests more heavily congested activity centers (NCRTPB 2020). Thus, the automobile route solver negotiates around such areas of higher parking penalties, with respect to the shortest physical path. Route length is the default cost variable for both travel modes, and the additional elements assigned to each route analysis layer refine the results.

These services are written in the C# programming language on the MS .NET Framework, in code modules constructed by the author, using an SOE code base provisioned by Esri. The ArcMap-based runtime API and the ArcObjects SDK for the .NET framework build and package these custom modules into a file that is uploaded to the primary map service. The end result is essentially middleware-as-a-service (MWAAS). Esri documentation states that ArcGIS Server 10.9.1 does have ArcMap runtime services, on which most .NET SOE development patterns back to version 10.5.1 are fully supported (Esri 2022). The cited documentation, here, also provides guidance for converting ArcMap-based SOE installations to use the ArcGIS Pro runtime. In the next phase of this project, one of the early steps in this process will be to transition the .NET ArcObjects-based SOE to be built with the ArcGIS Enterprise SDK.

CONCLUSIONS AND ACTION ITEMS

The *Commute GeoCalculator* server extension is functional over heterogenous urban settlement patterns in terms of street connectivity, transit accessibility, system mobility, service frequency, and the various costs of traversing the system at peak and off-peak traffic intervals. It is well suited for hosting in a standard enterprise-level IT environment or research lab. Transportation web and mobile applications that are purposed for quantifying multimodal travel would readily benefit from consumption of the project's services. High-volume data generation scripts could submit predefined lists of random and independent OD coordinate pairs with time ranges, to then write the returned trip cost information to a database. Transit agencies that are interested in analyzing the network performance of their route plans would benefit from this utilization. These services may also support data preparation for inferential statistics, often seen in spatial analyses. While the linearized data in the project's model are suitable for network analysis, methods for spatial analysis of linear traffic patterns are found in transportation research (Haixiang, Yang, and Yonghui 2010; Bhat and Zhao 2002). In addition, the next project phase is on track to create the third tier and advance the solution to a VGI system for travel mode choice. This will create a new set of use cases for researchers and transportation managers.

Meeting all of these system objectives will require ongoing support from the development community. To that end, before the next project phase produces the first mode-choice VGI, an online consortium will be deployed for the exchange of code, knowledge, and ideas to supplement the project's current open source GIT hub repository. This will be provided in conjunction with this code repository and service links delivered by the current project. These combined actions amount to the first critical steps on a long journey toward breaking pervasive dependency upon automobiles. To summarize, these steps will result in a collaborative, scalable web GIS that (1) informs the public of travel cost alternatives, and (2) allows the public to then provide ground truth data on travel behavior. Addressing automobile dependency is an incredibly complicated challenge requiring coordinated, intensive efforts across multiple disciplines. While pockets of progress can be found, it is a global challenge which continues to grow at regional and megaregional scales. Through a shared engagement in the processes to be set in motion by this project, perhaps the effectiveness of transportation interventions may be fully realized.

Commute GeoCalculator (CGC) Code Repositories:

Tier 1 – https://github.com/mrharthan/Scripts.git

Tier 2 – https://github.com/mrharthan/CGCLocator.git

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