SAN JOAQUIN VALLEY VISIONEVAL MODEL DOCUMENTATION

Report Title:

San Joaquin Valley VisionEval Model Documentation

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Report Prepared for:

Fresno Council of Governments

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

1.0 INTRODUCTION

1.1 OVERVIEW

The Fresno Council of Governments (FCOG) convened the eight Metropolitan Planning Organizations (MPOs) in the San Joaquin Valley region to develop a shared regional strategic travel demand model using the VisionEval software package. The model is referred to as the San Joaquin Valley VisionEval model or SJV-VE for short.

VisionEval is an alternative model design to traditional network-based travel demand models. The model is designed to produce per capita measures of vehicle miles traveled (VMT) and GHG but is also sensitive to changes in demographics, active travel, teleworking, and vehicle fleet options that are relevant for the San Joaquin Valley region.

Each MPO in the study region produces a long-range plan referred to as a Regional Transportation Plan (RTP) designed to identify regional priorities that align federal and state funds with local priorities and identify how the region will achieve environmental and transportation goals using forecasts for land use, population, transportation investments, and other policies. The MPOs in the study area have adopted RTPs that cover the future planning horizon out to the year 2046. The SJV-VE is designed to reflect the same inputs that these plans have developed for socio-economic and demographic data, the levels of transportation investments and infrastructure, and policies that are in place during the base year of 2022 and anticipated during the future planning year of 2046. The SJV-VE provides an alternative perspective on travel demand and reflects the policies and forecasts in the eight RTPs of each MPO in the San Joaquin Valley. It is designed to assist in understanding the impacts of land use, demographics, and policy changes on travel behavior, greenhouse gas (GHG) reduction, and socioeconomic impact.

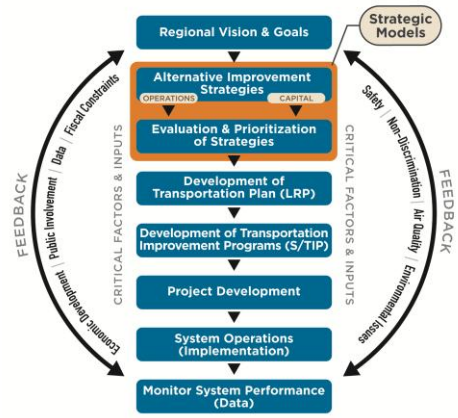
The report includes the following sections documenting the development of the SJV-VE model and the resulting findings from the model:

- Chapter 1 is a summary of the VisionEval tool.
- Chapter 2 a summary of the VisionEval reference model including inputs, model design, and reference model results.
- Chapter 3 summarizes the scenario analysis.

1.2 VISIONEVAL INTRODUCTION

The VisionEval model developed for the Valley supports the analysis of San Joaquin Valley MPO's residents' household travel behavior. This document sets out the scenarios that are tested in VisionEval and the inputs that define each of those scenarios.

FIGURE 1: FHWA PLANNING PROCESS



VisionEval is a widely used tool for evaluating transportation policies and projects and has been employed in a variety of settings across the United States. It offers a flexible framework that can be used to analyze a range of policy options and transportation scenarios. VisionEval has been used by several state and regional planning agencies. It is often used in exploratory or "scenario" planning processes that test variations in policies and demographics, as the case of the San Joaquin Valley region.

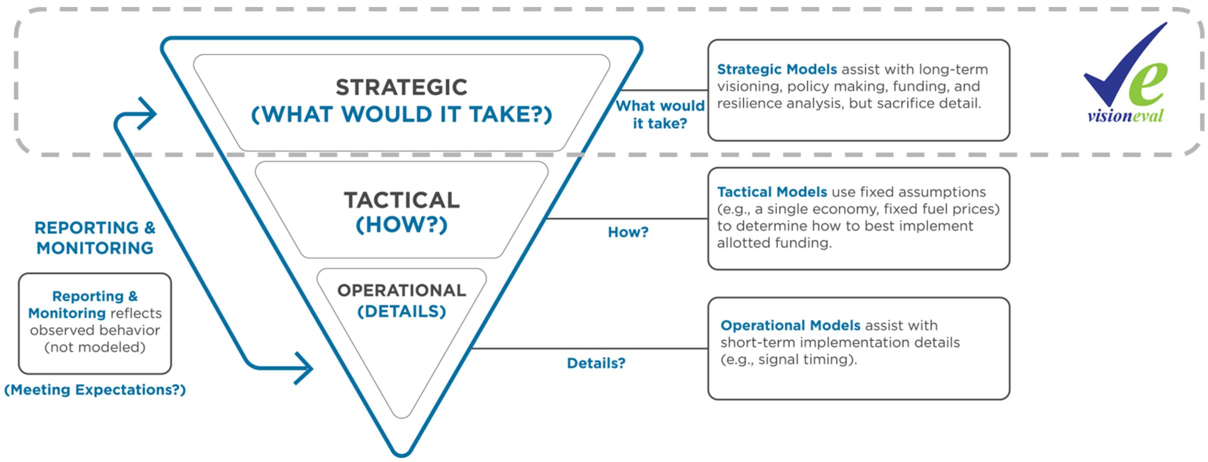
The model is typically used to assess a wide range of policy and pricing effects on household travel modes and preferences, including travel by automobile, transit, bicycle, and walking. In addition, VisionEval includes built-in metrics and analytical methods to summarize travel behavior changes as a result of land use changes and other influences such as policy changes, pricing, and vehicle fleet changes. VisionEval does not assess network impacts or precisely localized land use impacts and instead creates a broader picture of geographies within the model region. This makes VisionEval ideal for strategic modeling practices that assess specific performance metrics including VMT or GHG (the model produces many other measures).

Transportation planning models can be categorized into three levels, as shown in Figure 2~~Figure 2~~: strategic, tactical, and operational. VisionEval is strategic model - an econometric approach to travel modeling using nationally estimated data on household-based characteristics combined with local data including attributes of the built environment in combination with the supply of available transportation modes, infrastructure, pricing, and policies that influence travel behavior. It is an aggregated supply and disaggregated demand model, using zonal level data to represent the amount and availability of travel infrastructure (i.e., supply) and a detailed synthetic representation of daily travel demand at the household level. By not assigning daily travel (or individual trips) to specific links on the network, the model runs faster to quickly produce household-level estimates of travel demand that can be aggregated to zonal estimates of behavior. This structure makes the model ideal for "top of the funnel" analysis as shown in Figure 2~~Figure 2~~ because of its flexibility, speed, and ability to explore uncertainty and assess likely impacts of "what if" questions.

Traditional travel demand models that assign trips to a network can be referred to as tactical models. These models are better suited for assessing more engineering-level questions such as how many users may be on a particular link, or how will roadway congestion or operations change as a result of changing other inputs? For instance, most trip-based travel demand models are less sensitive to changes in pricing or factors that may change individual households trip generation potential.

Operational models are often used for detailed and more short-term operational questions. These models require a specific forecast for subareas of the model region and are insensitive or ignorant to larger changes in demand that may occur with population changes or the price of fuel. Microsimulation is an example of an operational model.

FIGURE 2: VISIONEVAL IN CONTEXT TO OTHER MODELS



Source: Oregon DOT, adapted by RSG

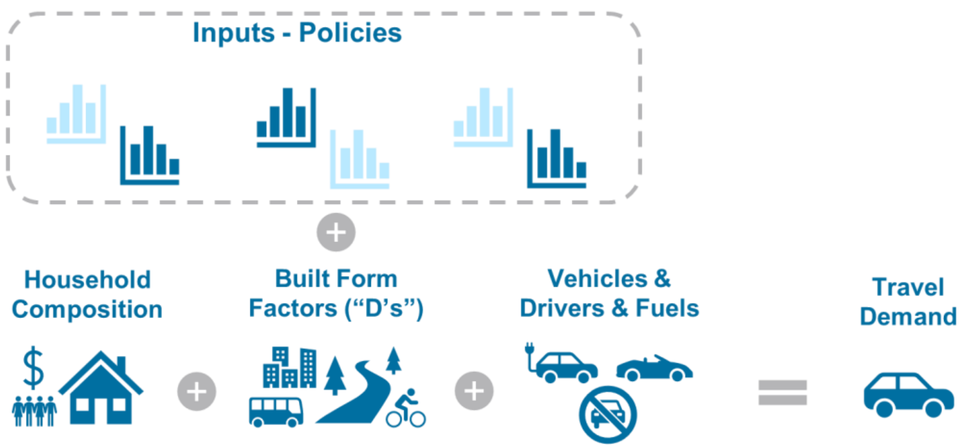
VisionEval estimates demand by using a nationally estimated set of data at the census block group level from the National Household Travel Survey (NHTS). Each of the sub-models in the VisionEval design requires inputs that inform key characteristics of the household and its relationship to the area around it. VisionEval uses a sequence of modules that apply input data to build a composite representation of these characteristics for each household in the model region and from those household characteristics, estimate travel demand. This process follows four main steps:

- 1) Define the number and location of households, including key attributes such as the number of persons, their ages, employment status, occupation type, and income.
- 2) Determine the attributes of the area surrounding each household, including walkability, transit frequency, arterial and freeway lane miles, the share of active travel in each zone, household and employment density, ratio of jobs to households, the ratio of single-family to multi-family units, and many other factors.

- 3) Assign travel modes and vehicle ownership to each household. Household characteristics and built form inputs inform whether households are more likely to share vehicles, have one car per driver or own no vehicles, own vehicles of a certain powertrain and age, and so on.
- 4) Define the pricing and policies that influence travel demand in the region. Establish key inputs that affect demand for travel such as fuel prices, parking costs, travel demand management incentives, congestion pricing, and other policies and pricing inputs that may exist in the region.

The result is an estimate of daily travel demand for each household in the model region for each of the model years for which inputs are provided.

FIGURE 3: VISIONEVAL ESTIMATED DEMAND PROCESS



VisionEval also contains a Multiscenario scenario framework that allows users to run hundreds of scenarios with variations that represent possible futures. This setup is ideal for testing travel outcomes under uncertainty by providing insight into unique or potentially unexpected "what if" scenarios for the model region. RSG has developed dashboard tools using Shiny for efficiently running a Multiscenario analysis, and for analyzing and comparing outcomes for various scenarios as detailed in chapters 3 and 4.

2.0 SAN JOAQUIN VALLEY REFERENCE MODEL

The San Joaquin Valley VisionEval strategic travel demand model is used as a critical and important tool to help identify and assess the impact of state and local actions that can affect household travel behavior and reduce regional GHG emissions. The tool is designed to run several unique scenarios using variations in the land use modules that create different possible futures. This first requires building a baseline or reference case model.

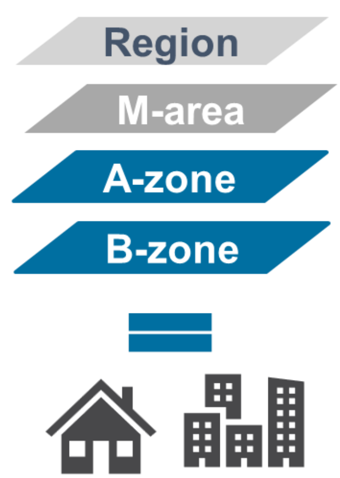
Establishing a reference model is key to understanding the impacts of varied policies and actions that can affect travel outcomes. The San Joaquin Valley VisionEval reference model uses the socioeconomic data from the 2022 RTP travel models of each of the eight MPOs in the San Joaquin Valley to represent both current and forecasted travel conditions and demographics for 2022 and 2046. The following section describes the model geographies, the inputs used and how they are derived, and the general setup used for the reference model.

2.1 GEOGRAPHY

VisionEval is divided into the following geographies, each dictating the geographic resolution of various inputs and outputs:

- Region: The entire area covered by the VisionEval model.
- Marea: The metropolitan areas within the VisionEval model. For the San Joaquin Valley model, the Mareas represent MPO boundaries. The MPOs included in this model are Fresno Council of Governments (FCOG), Kern Council of Governments (KCOG), Kings County Association of Governments (KCAG), Merced County Association of Governments (MCAG), Madera County Transportation Commission (MCTC), San Joaquin Council of Governments (SJCOG), Stanislaus Council of Governments (StanCOG), and Tulare County Association of Governments (TCAG). The external zones are classified as Mareas but are not included in the primary area of analysis.
- Azone: Larger geographic areas such as cities or counties. The SJV model uses a combination of urbanized areas and 2020 Census Tracts to divide the Mareas into Azones.

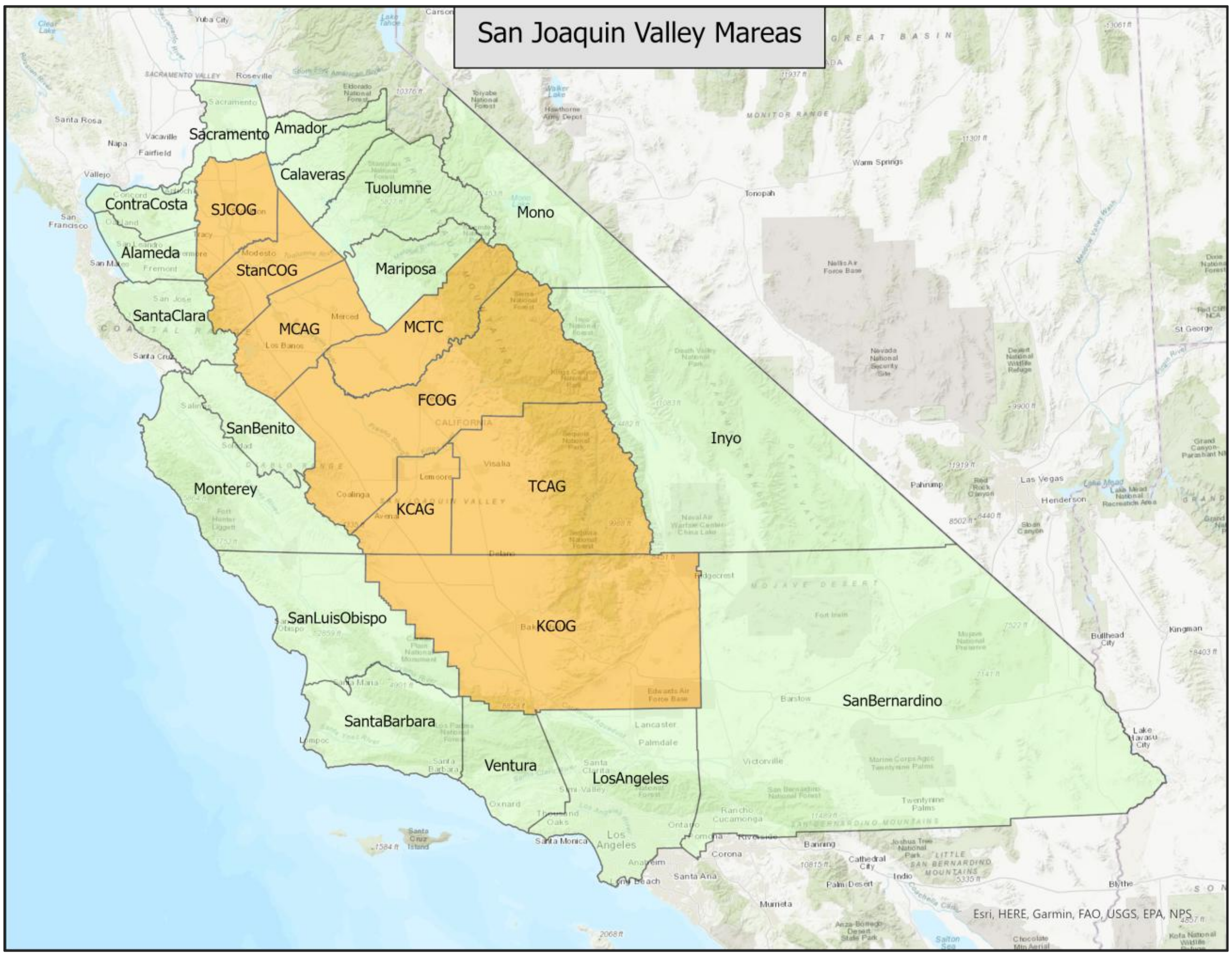
Different VisionEval inputs are entered at each geographic level.



- Bzone: Subivisions of Azones that are used to represent individual neighborhoods or sub-county areas such as Census Block Groups. The SJV Bzones are adapted from 2020 Census Block Groups.

Figure 4~~Figure 4~~ shows the VisionEval model geographies for the San Joaquin Valley model region.

FIGURE 4: VISIONEVAL MAREAS FOR THE SAN JOAQUIN VALLEY MODEL



The San Joaquin Valley model contains 25 unique Mareas, 256 Azones, and 2,746 total Bzones. A summary of these Mareas and their Azone and Bzone subdivisions can be found in Table 1~~Table 1~~. The external zones are used to capture the travel behavior for:

- Commuters that live in the San Joaquin Valley but commute to an area outside the Valley for work.

- Commuters that live outside the San Joaquin Valley and commute into the San Joaquin Valley for work.

TABLE 1: SAN JOAQUIN VALLEY ZONES

MAREA	NUMBER OF AZONES	NUMBER OF BZONES
FCOG	49	636
KCAG	12	84
KCOG	44	600
MCAG	23	164
MCTC	15	98
SJCOG	30	501
StanCOG	26	341
TCAG	40	305
External zones	17	17
Total	**256**	**2746**

Commuter Shed Analysis

To understand the extent of the San Joaquin Valley commuter shed, RSG used the 2020 Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data to study flows both into and outside of the San Joaquin Valley region. The dataset provides information on the home and work location of workers at the block group level and were aggregated to the county level.

Table 2~~Table 2~~ summarizes the home and work locations of all the people that work in San Joaquin Valley. There are 1,054,248 workers in the region, of which 85% live in San Joaquin Valley counties while the rest live in bordering counties. The latter represent a significant share of workers that commute into the region.

TABLE 2: SAN JOAQUIN VALLEY WORKERS BY HOME LOCATION

WORK COUNTY	WORKERS THAT LIVE IN SJV	WORKERS THAT LIVE IN BORDERING COUNTIES	TOTAL NUMBER OF WORKERS
Fresno	256,238	30,420	286,658
Kern	174,457	31,738	206,195
Kings	24,760	3,107	27,867
Madera	29,062	3,750	32,812
Merced	44,562	6,787	51,349
San Joaquin	144,839	51,458	196,297

Stanislaus	119,156	21,660	140,816
Tulare	100,912	11,342	112,254
TOTAL	**893,986 (85%)**	**160,262 (15%)**	**1,054,248 (100%)**

Figure 5~~Figure 5~~ further breaks down workers commuting into San Joaquin Valley by county. Out of all workers that work in San Joaquin Valley and live in a bordering county, the majority reside in Los Angeles (35,283 or 3.35%) or Sacramento (28,188 or 2.67%).

FIGURE 5. SAN JOAQUIN VALLEY WORKERS THAT LIVE IN BORDERING COUNTIES

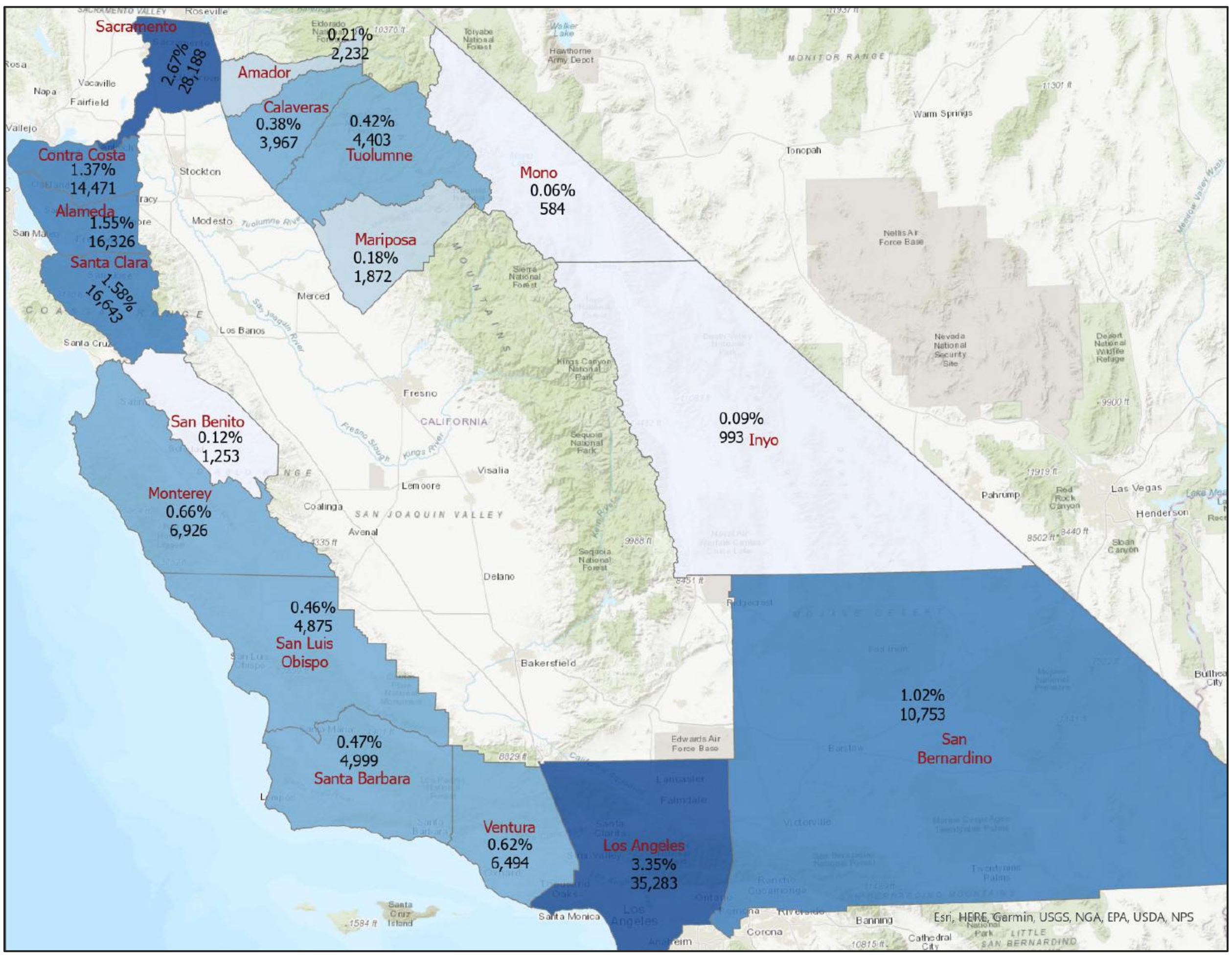
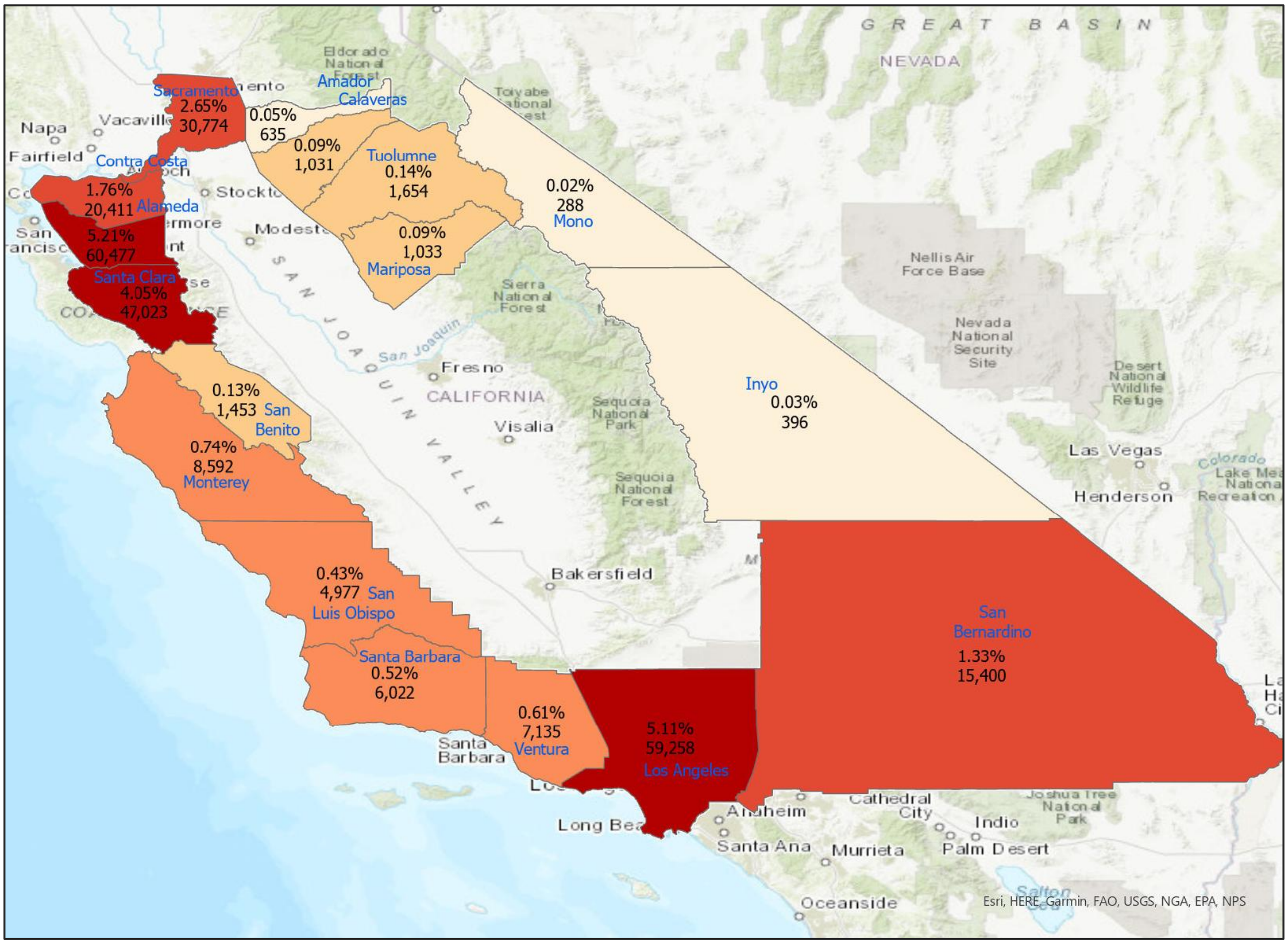


Figure 6~~Figure 6~~ shows the number and percentage of San Joaquin Valley employed residents that work outside of San Joaquin Valley. It can be observed that out of all employed residents in the San Joaquin Valley, 60,477 (5.21%) work in Alameda County, 59,258 (5.11%) work in Los Angeles County, and 47,023 (4.05%) in Santa Clara County, making these counties the most popular work destinations for San Joaquin Valley residents that work outside of the region. Such workers number up to 166,758.

FIGURE 6. SAN JOAQUIN VALLEY RESIDENTS THAT COMMUTE TO BORDERING COUNTIES



Given the significant commuter flows between San Joaquin Valley counties and adjacent border counties, the model incorporates border-county workers to account for their travel patterns and impacts on the region.

2.2 INPUTS

VisionEval uses a series of input files to inform the model for each of the analysis years. There are 65 input files including nearly three hundred input parameters. Generally, the inputs can be classified into these general categories:

- Setup files: Required as basic parameters for VisionEval. These values do not change.

- Demographics inputs: Population and employee demographics and composition for the model region.
- Land use inputs: Housing and developable land inputs to inform potential travel demand growth.
- Systems operations/ITS inputs: Inputs that define the level of system efficiencies and ITS technology deployment.
- Transportation options inputs: Policy inputs that impact transportation options available to households.
- Vehicles and fuels inputs: Inputs that alter the vehicle fleet and fuel mix available to or used by households.
- Pricing inputs: Inputs that create additional costs for system users through policies or market factors such as congestion charges, fuel prices, or parking costs.

Table 3~~Table 3~~ shows the list of inputs organized by input type.

TABLE 3: VE INPUT FILES FOR REGIONAL MODELING

CATEGORY	INPUT	DESCRIPTION	GEO
Setup	units.csv	Describes the default units to be used for storing complex data types in the model. This file should not be modified by the user	Model
Setup	Deflators.csv	Annual deflator values (e.g. consumer price index) that convert currency values between different years. Must include 1999, base year and other years referenced in inputs. Source: Oregon CPI-Urban areas. Not commonly updated.	Model
Setup	geo.csv	Geographic relationships (Azone, Bzone, and Marea) with names. Note that non-MPO counties can be "associated" with an MPO, as part of its commute shed. Names should remain consistent with the input data.	Model
Setup	model_parameters.json	Global parameters including Value of Time. This file should not be modified by the user.	Model
Setup	bzone_lat_lon.csv	Bzone Centroid Latitude/Longitude by year by Bzone	Bzone
Setup	azone_fuel_power_cost.csv	Vehicle energy costs for fuel ($/gallon), electricity ($/kwhr) by year by Azone (exclusive of taxes)	Azone
Setup	marea_base_year_dvmt.csv	Optional File: Marea DVMT by type (LDV, HD Truck) overwrite of base year 2010 Hwy Statistics default (NA recommended for VE-RSPM) and urbanized area name	Marea
Setup	marea_safety_factors.csv	Crashes per 100 million miles traveled for autos, transit, and active travel modes.	Marea
Setup	region_base_year_dvmt.csv	Region Freight Vehicle DVMT growth rates-basis (Commercial service, population, income, or household DVMT; Heavy truck based on population or income) and overwrite of base year 2010 Hwy Statistics default of region Heavy Truck	Region

		DVMT (NA recommended for VE-RSPM) and state name.	
Setup	region_hh_driver_adjust_prop.csv	Licensed share of driving age persons in 5 age groups relative to model estimation year (2001 NHTS) by year modelwide (default =1.0)	Region
Setup	region_car_svc_propensity_coef.csv	Parameter file with model estimating households propensity for using shared car services.	Region
Setup	region_road_cost.csv	Infrastructure costs (BaseModernization, PreservationOpsMtncc, Other, Arterial per LnMi, Fwy per LnMi) used to estimate LDV VMT fee to fully recover road costs.	Region
Demographics	azone_gq_pop_by_age.csv	Number of Non-Institutional Group Quarters persons by 6 age groups by year by Azone	Azone
Demographics	azone_hh_pop_by_age.csv	Number of Household persons within 6 age groups by year by Azone	Azone
Demographics	azone_hhsize_targets.csv	Average household size & share of 1-person households by year by Azone	Azone
Demographics	azone_per_cap_inc.csv	Annual Per Capita Income by type (household or HH vs. group quarters or GQ) by Year by Azone	Azone
Demographics	azone_wkr_loc_type_occupation_prop.csv	The ratio of workers to persons by age cohort in the model year relative to the model estimation data year (Optional file).	Azone
Land Use	bzone_unprotected_area.csv	Land Area (water and large protected lands removed) by location type (Urban, Town, Rural) by year by Bzone	Bzone
Land Use	bzone_dwelling_units.csv	Number of Dwelling Units by type (single family or SF, multi-family or MF, GQ) by Year by Bzone	Bzone
Land Use	bzone_employment.csv	Number of Total, Retail, and Service employees by year by Bzone	Bzone
Land Use	bzone_hh_inc_qrtl_prop.csv	Share of Dwelling Units (HHs) in Per Capita Income quartiles by year by Bzone	Bzone
Land Use	bzone_network_design.csv	“Design D” (D3bpo4, a pedestrian-oriented network measure as defined by EPA Smart Location Database) by year by Bzone	Bzone
Land Use	bzone_parking.csv	Parking restrictions: Free spaces per dwelling unit type (SF, MF, GQ), share of workers paying for parking and in cashout program, and average parking fee by Year by Bzone	Bzone
Land Use	bzone_urban-mixed-use_prop.csv	Share of HHs in Urban Mixed Use Neighborhoods by Year and Bzone (uses the NHTS Claritas Urban Mixed Use definition)	Bzone
Land Use	bzone_urban-town_du_proportions.csv	Share of Bzone Dwelling units (SF, MF, GQ) within urban and town location types by year	Bzone
Transportation Options	bzone_carsvc_availability.csv	Car Service level of service (High, Low) by Year by Bzone	Bzone
Transportation Options	bzone_transit_service.csv	“Transit D” (D4c, accessible hourly PM peak service frequency as defined by EPA Smart Location Database) by year and Bzone	Bzone
Transportation Options	bzone_travel_demand_mgt.csv	Share of participants in home Individualized Marketing programs (HHs) and work-based Transportation Demand Management programs (workers) by year by Bzone	Bzone
Transportation Options	azone_prop_sov_dvmt_diverted.csv	Goals for percentage of single-occupancy vehicle DVMT that is diverted to active travel modes within a 20 mile tour	Azone
Transportation Options	azone_carsvc_characteristics.csv	Car Service Rate ($/mile) by level (high, low, ave), average Car service vehicle age, and limits on shifting to car service (LtTruck, Auto) by Year by Azone	Azone

Transportation Options	azone_vehicle_access_times.csv	Minutes to call-up vehicles arrival by type (owned, High/Low CarSvc) by year by Azone	Azone
Transportation Options	marea_transit_service.csv	Annual Transit Service revenue-miles by service mode (demand responsive, bus, rail, etcl) by year, and Marea.	Marea
Transportation Options	region_carsvc_shd_occup.csv	Average Occupancy of shared car services	Region
Transportation Options	region_telework.csv	Describes the levels of teleworking observed within the different occupation types	Region
Pricing	azone_payd_insurance_prop.csv	Share of HHs in Pay-as-you-Drive Auto Insurance programs by Year by Azone	Azone
Pricing	azone_hh_veh_own_taxes.csv	Annual auto ownership fees (fixed and sales tax rate) by Year by Azone	Azone
Pricing	Azone_veh_use_taxes.csv	Mileage Based Fee by type (fuel tax, VMT fee, Ev surcharge) by year by Azone	Azone
Pricing	Marea_congestion_charges.csv	Congestion Charges ($/mile) coverage of daily VMT by road type (Fwy, Arterial) by five congestion levels by year by Marea	Marea
Pricing	region_co2e_costs.csv	Optional: Environmental and social cost of CO2e emissions per metric ton carbon by year model wide.	Region
Pricing	region_prop_externalities_paid.csv	Share of Social Externalities covered in household fees (carbon, other) by year model wide	Region
Veh/Fuels	azone_charging_availability.csv	Availability (0 to 1) of vehicle charging by dwelling type (SF, MF, GQ) by stock year by Azone	Azone
Veh/Fuels	azone_electricity_carbon_intensity.csv	Carbon Intensity of Electricity (g/MJ) by stock year by Azone	Azone
Veh/Fuels	azone_hh_lttrk_prop.csv	Share of household light-duty vehicles (LDV) that are Light Trucks by year by Azone	Azone
Veh/Fuels	azone_hh_veh_mean_age.csv	Mean Age of household vehicles by type (auto, light truck) by year by Azone.	Azone
Veh/Fuels	marea_transit_ave_fuel_carbon_inten.csv	Carbon Intensity of composite Transit Fuel (g/MJ) by stock year and Marea	Marea
Veh/Fuels	marea_transit_biofuel_mix.csv	Biofuels share of Transit fuels (ethanol, biodiesel, renewable natural gas) by stock year and Marea	Marea
Veh/Fuels	marea_transit_fuel.csv	Fuel mix (share of GGE) for Transit Vehicles (Van, Bus, Rail) for ICE/HEV (diesel, gas, compressed natural gas) by stock year	Marea
Veh/Fuels	marea_transit_powertrain_prop.csv	Powertrain mix (share of ICE, HEV, EV DVMT) for Transit Veh (Van, Bus, Rail) by stock year and Marea	Marea
Veh/Fuels	region_av_lev5_parameter.csv	Various inputs for guiding the behaviors of self driving vehicles.	Region
Veh/Fuels	region_av_lev5_propensity_coef.csv	Logit model coefficients for identifying the relative household propensity to be interested in a Level 5 fully self driving vehicle.	Region
Veh/Fuels	region_av_market_share.csv	Share of vehicle fleets between human driving L0, human driven but with connected attributes (L3), and fully self driving (L5).	Region
Veh/Fuels	region_ave_fuel_carbon_intensity.csv	LDV (HH, CarSvc, ComSvc, Van) + HD (Truck, Bus, Rail) composite carbon Intensity of Fuel (g/MJ) by stock year by Marea	Region
Veh/Fuels	region_carsvc_powertrain_prop.csv	LDV - Car service Vehicle (Auto/Light Truck) powertrain (Ice/Hev/Phev/Bev) shares by stock year by Marea.	Region
Veh/Fuels	region_comsvc_lttrk_prop.csv	LDV - ComSvc share of vehicles that are Light Truck by stock year	Region
Veh/Fuels	region_comsvc_powertrain_prop.csv	LDV-ComSvc Vehicle (Auto/Light Truck) powertrain (ICE/HEV/BEV) shares by stock year by Marea	Region
Veh/Fuels	region_comsvc_veh_mean_age.csv	Average age of all commercial vehicles in the model region	Region

Veh/Fuels	region_hvytrk_powertrain_prop.csv	Starting share of DVMT by type (LDV, HvyTrk, Bus) by road type (Fwy,Arterial, other). Note that LDV share is adjusted by congestion model.	Region
Veh/Fuels	region_driverless_veh_parameter.csv	Driverless parameters	Region
Veh/Fuels	region_driverless_veh_prop.csv	Proportion of driverless vehicles for non-household vehicles.	Region
Systems Operations/ITS	marea_dvmt_split_by_road_class.csv	Starting share of DVMT by type (LDV, HvyTrk, Bus) by road type (Fwy, Arterial, other), LDV share is adjusted by the congestion model.	Marea
Systems Operations/ITS	marea_lane_miles.csv	Freeway and arterial lane-miles by year and metropolitan area	Marea
Systems Operations/ITS	marea_speed_smooth_ecodrive.csv	Deployment (0-1,1=100%VMT coverage) of Speed Smoothing (Fwys, Arterials) and Eco-Driving (LDV, HD Trucks) programs by year by Marea	Marea
Systems Operations/ITS	marea_operations_deployment.csv	Deployment (0-1,1=100%VMT coverage) of operations programs on Fwy (Ramp metering, Incident Response) and Arterials (Signal Coordination, Access Mgmt) programs by year by Marea	Marea
Systems Operations/ITS	other_ops_effectiveness.csv	Optional File: Delay reduction (0-1) anticipated with full deployment of user-defined other operations program by road type (Fwy, Art), congestion type (Reoccurring, non-reoccurring) by 5 congestion levels by year by Azone	None

2.3 MODEL SETUP

The reference model reflects the conditions of the 2022 travel models for each MPO and is calibrated to a base year of 2022 and future year of 2046. This includes demographic forecasts, transit and roadway networks, and supplemental empirical data sources such as the American Community Survey (ACS), Highway Performance Monitoring System (HPMS), and EPA Smart Location Database (SLD). The following summarizes the VisionEval (VE) setup and model input files for the reference scenario.

Model Run Script

The reference model uses the following VisionEval packages:

- Population Sim: SJV-VE uses the Population Sim module of VisionEval to create a synthetic population for the model region. This package was customized to estimate households in the synthetic population used for the San Joaquin Valley region. PopulationSim was used rather than the default SimHouseholds package to align with other modeling efforts in the study area that use the open-source population synthesis process. The activity-based models being developed for Fresno and Tulare are using PopulationSim. In addition, Population Sim can be used to incorporate additional US ACS variables and append those characteristics to the households in the VisionEval model. These often include English language proficiency, disability, and others. While they are not used to inform travel behavior decisions, they can be appended to the households allowing for queries and downstream analysis to compare travel behaviors across these other dimensions.

- Sim Households (not used): VisionEval can use the Sim Households package to synthesize households within model Azones. This household synthesis is estimated using 2020 PUMS data for the San Joaquin Valley region. This package was superseded with Population Sim for this model. (VESimHouseholdsSJV)
- Land Use: VisionEval uses a land use module to assign employment, households, and land use types to Bzones across the model region. This custom version of the package is adjusted to run with the San Joaquin Valley model. (VELandUseSJV)
- Powertrains: The powertrains package adjusts the proportion of household vehicles sales by powertrain (internal combustion, hybrid, battery electric, and plug-in hybrids) for a model year. This is customized to the San Joaquin Valley model region using local vehicle registration data. It also accounts for changes in electric vehicle sales that require 100% new passenger vehicles to be zero-emission vehicles by 2035.[1] (VEPowertrainsAndFuelsSJV)
- Travel Demand Work From Home: Estimates how many workers work from home. This uses the Multimodal Module estimated using 2017 NHTS data (VETravelDemandWFH).
- Driverless packages: Packages which reflect updates to the driverless and car service modules. Level 3 and Level 5 automation can be modeled. Shared (e.g., Uber Pool) and unshared (typical single rider) ride hailing (car service) with different occupancies and price points (VELandUseDL and VETravelPerformanceDL). The Connected and Automated vehicle inputs in the reference model presume 60% of the vehicle fleet is L3, 40% human L0, and 0% automated L5.
- Safety: The package VETravelPerformanceDL includes a safety module that accounts for changes in serious and fatal crashes due to input policies and strategies. (VETravelPerformanceDL)

Population Sim

VisionEval and PopulationSim are complementary tools that address critical aspects of transportation modeling and population synthesis. PopulationSim is an open-source platform for population synthesis, generating realistic synthetic populations from census data and user-defined control variables with outputs designed to support transportation planning needs.[2]

[1] https://ww2.arb.ca.gov/our-work/programs/drive-forward-light-duty-vehicle-program/advanced-clean-cars

[2] https://activitysim.github.io/populationsim/

VisionEval has been revised to include a module that incorporates PopulationSim output as its source of synthetic population inputs.[3]

Setup and Data Requirements

Population Sim generates datasets of households and individuals for travel demand models using a seed sample from Census Public Use Micro Data Sample (PUMS) and control totals to align demographic and attributes with regional targets. The control totals are flexible and can be applied at various geographic levels. The control distributions can be derived from the base year Census data distributions or can be derived from a future forecasted population.

Setting up Population Sim involves several steps to define the population framework and data inputs:

Define total households at smallest geography: Determine the total number of households at the smallest geographic unit, such as Traffic Analysis Zones (TAZs), block groups or in this case Bzones for VE.

Select marginal control variables: Choose targets that Population Sim will match, typically including household size, number of workers in the household, household income ranges, and age distribution bins. Additional variables, such as race, occupation, language proficiency, or presence of children, can be included depending on needs.

Build marginal control distributions: For the base year, derive distributions directly from Census tables. Apply these distributions to household or person control totals. For future years, either scale the base year distributions or use forecasted data to ensure consistency with future population assumptions.

Assign geographic levels: The basic control is total households at the smallest geography (e.g., TAZs or block groups). The user typically sets Population Sim to apply the other control distributions at higher geographic levels, such as block groups or tracts, as appropriate given the control data source.

Appendix A contains the Population Sim outputs used in the VisionEval model. Income brackets in the Population Sim inputs were modified to match ACS and RTP forecasted income per capita for 2022.

VELandUse Package with Land Use Allocation

As noted above, VisionEval uses a land use module to assign employment, households, and land use types across the model region. The basic inputs are the number of single family and multi-family dwelling units and the number of jobs in each Bzone. The default land use package, unused in this application, in VisionEval works with asserted targets based the developed land

[3] https://github.com/VisionEval/VisionEval-Extras/tree/main/VEPopulationSim

use inputs, balancing households, jobs, population, income, and household size targets across Bzones.

The SJV-VE model incorporates a new version of the land use module. This new module is a draft release produced by a research team from Portland State University for Oregon Department of Transportation. as part of an ODOT research project. The module allows for simpler, more aggregate, dwelling and employment inputs to be used, which are then allocated to Bzones during the model run depending on the characteristics of the Bzones and other inputs. This makes the SJV-VE implementation sensitive to land use policy inputs and enhances its ability to test different possible future socio-economic and land use scenarios more quickly.

The new land use module instead allocates dwelling unit and employment inputs in terms of total households and jobs by land use type. Each Bzone is allocated to a land use type, which is defined by a combination of its development density (divided into four bands, center, inner, outer, and fringe) and its land use diversity, which is a measure of land use mix (for example, more residential focused or more commercial development focused)

The reference model described later in this section used the typical exogenously derived Bzone inputs approach, as did the majority of the scenarios run for this project. One set of land use scenarios were run with both the more flexible land use model allocation from land use type to Bzones and the typical exogenous Bzone inputs approach.

Powertrains Package

The VEPowertrainsAndFuels package can be customized to match the vehicle sales by powertrain type, fuel type, and vehicle year for the model region. Powertrain mixes can be adjusted to account for the proportion of vehicles that use internal combustion engines (ICEV), hybrid-electric engines (HEV), battery electric (BEV), or plug-in hybrid powertrains. Proportions of vehicles by fuel type can also be adjusted. Fuels include gasoline, diesel, and CNG. Vehicle types accounted for in this package include household vehicles (autos and light trucks), commercial vehicles, car service or ride hailing vehicles, and heavy trucks.

The powertrains package for the San Joaquin Valley model was customized using California DMV vehicle registration data for the model region for household vehicles and heavy trucks from 2019 to 2025. Car service vehicles were also adjusted to follow the same powertrain and fuel mixes as household vehicles. Household vehicles in this model are predominantly gasoline-powered ICE vehicles. Figure 7~~Figure 7~~ shows the proportion of household light duty automobiles by powertrain type for the San Joaquin Valley model region, and Figure 8~~Figure 8~~ shows the proportion of household light trucks. Future years were assumed to meet the goals outlined in CARB regulations on zero-emission vehicle sales.[4] Heavy truck powertrains were

[4] https://ww2.arb.ca.gov/our-work/programs/drive-forward-light-duty-vehicle-program/advanced-clean-cars

also updated to reflect the CARB Advanced Clean Trucks and Advanced Clean Fleets regulations, which aim for 75% of heavy truck vehicles being zero-emission vehicles by 2035, and 100% of all heavy truck fleet vehicles being zero-emission vehicles by 2045.[5]

FIGURE 7: PROPORTION OF HOUSEHOLD VEHICLES BY POWERTRAIN - AUTOS

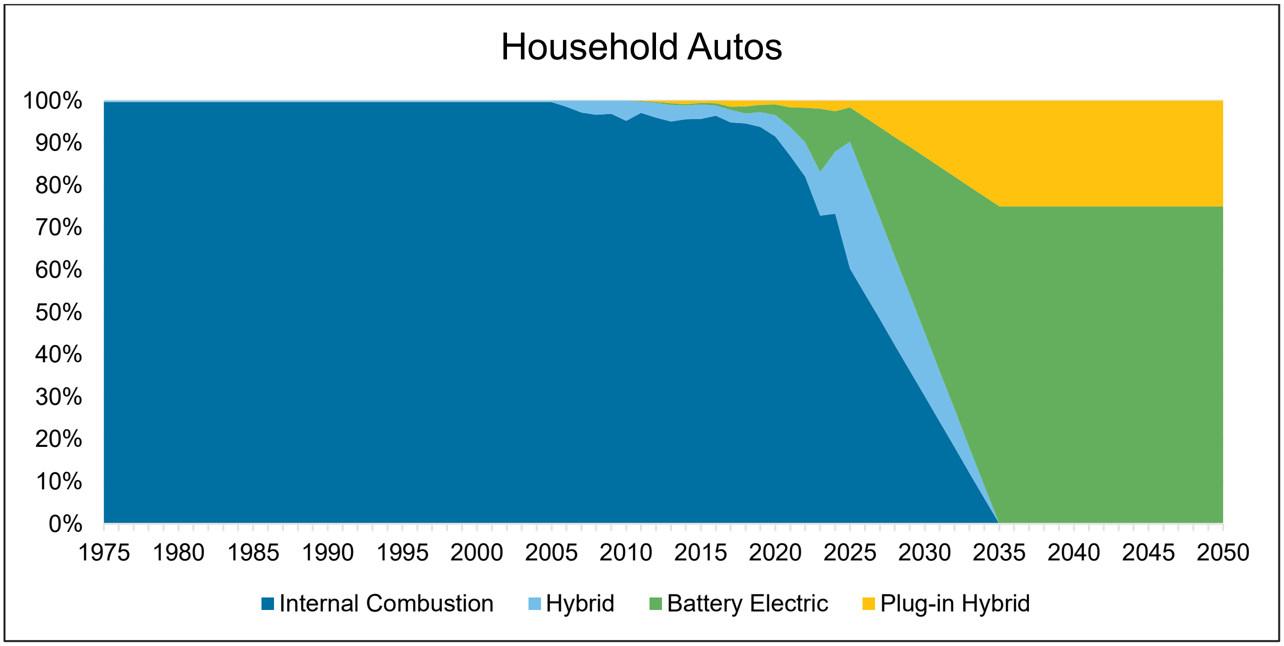
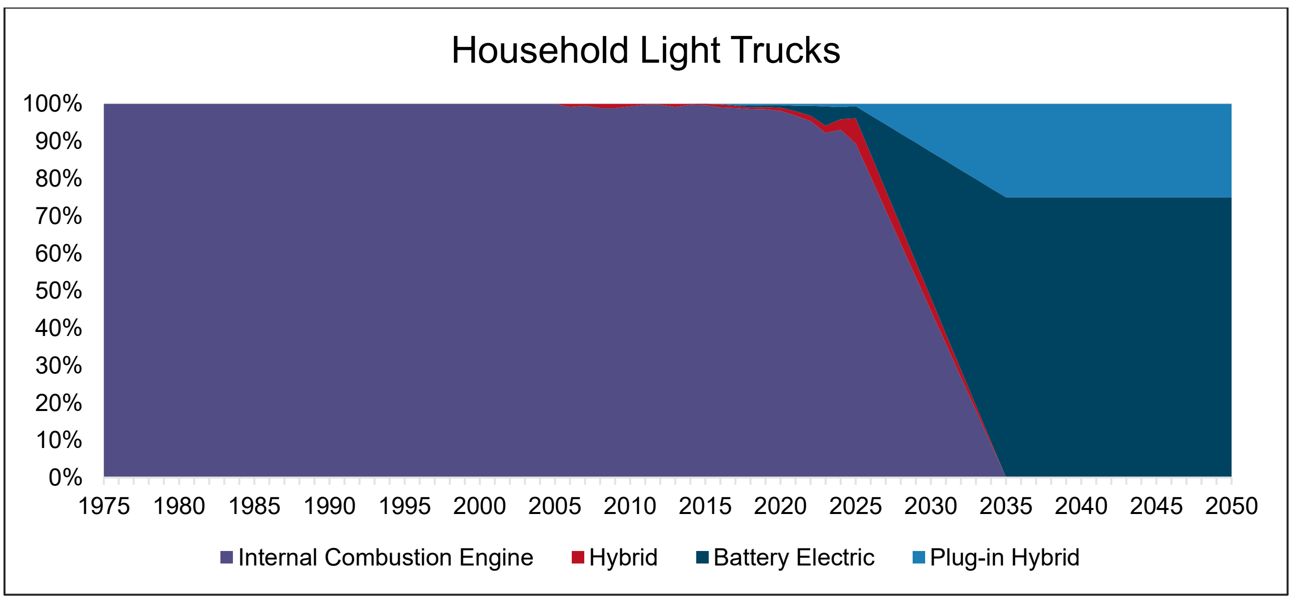
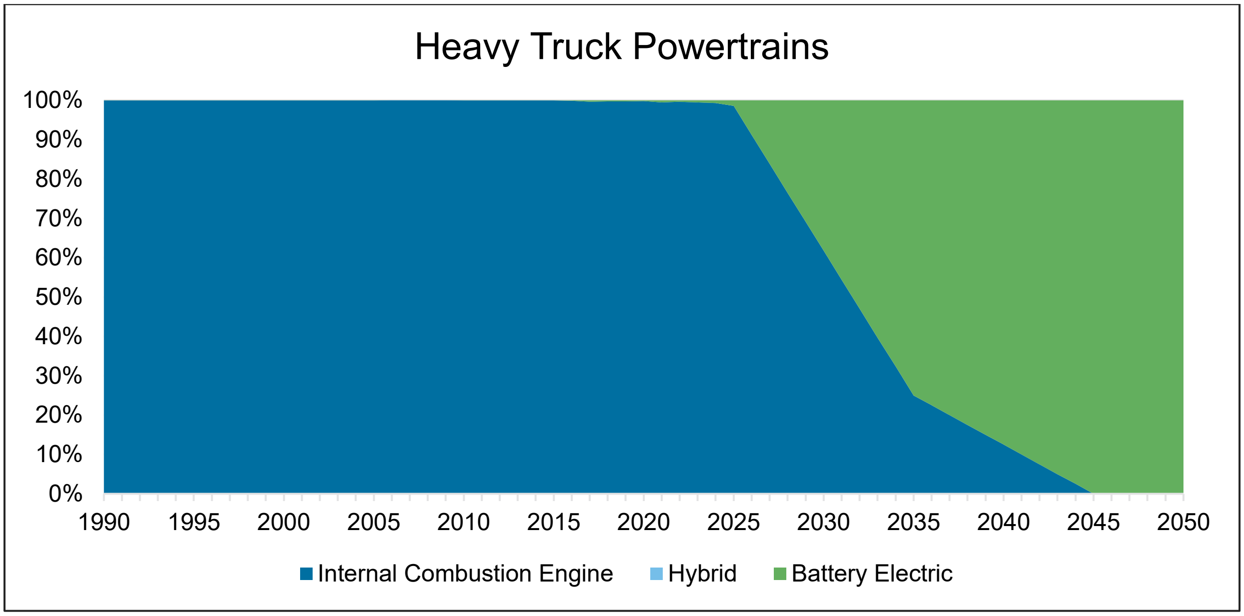


FIGURE 8: PROPORTION OF HOUSEHOLD VEHICLES BY POWERTRAIN – LIGHT TRUCKS



[5] https://ww2.arb.ca.gov/resources/documents/zero-emission-road-medium-and-heavy-duty-strategies

FIGURE 9: PROPORTION OF HEAVY TRUCKS BY POWERTRAIN



Note that the actual vehicle fleet mix is computed at runtime as a function of vehicle ownership rates, vehicle turnover rates, household income, and the availability of each vehicle type in each year that the household may be ready to purchase a vehicle. That computation is informed by the three charts above.

Reference Model Inputs

azone_carsvc_characteristics.csv

Category: Transportation Options

This input specifies car sharing service and ride hailing services at the Azone level. It is informed using car service costs calculated from the 2023 Central California Travel Study along with VisionEval default input values[6]:

- **HighCarSvcCost**: Average cost in dollars per mile for travel by high service level car service exclusive of the cost of fuel, road use taxes, and carbon taxes (and any other social costs charged to vehicle use). This was calculated as $2.26 per mile based on the Central California Travel Study.
- **LowCarSvcCost**: Average cost in dollars per mile for travel by low service level car service exclusive of the cost of fuel, road use taxes, and carbon taxes (and any other social costs charged to vehicle use). Low car service is typically associated with the per

[6] https://www.fresnocog.org/wp-content/uploads/2023/07/CCTS-HTS-Report_Final_2023.pdf

mile user costs for car sharing (fixed location or free-floating car service locations). This cost was estimated to be $3.96 per mile from the Central California Travel Study.

- **AveCarSvcVehicleAge**: Average age of car service vehicles in years. The average age of a San Joaquin Valley vehicle is 8 years. It may be expected that the car service vehicles are newer and may have a higher rate of vehicle turnover in the state at large. To match this expectation, it is assumed the average car service age in this input is 6 years.

TABLE 4: CAR SERVICE CHARACTERISTICS SUMMARY

CAR SERVICE	2022	2046
HighCarSvcCost.2020	$2.26	$2.26
LowCarSvcCost.2020	$3.96	$3.96
AveCarSvcVehicleAge	6	6
AutoCarSvcSubProp	95%	95%
LtTrkCarSvcSubProp	75%	75%
ShdCarSvcCost.2020	$2.00	$2.00
UnShdCarSvcCost.2020	$2.00	$2.00
LowCarSvcDeadheadProp	0%	0%
HighCarSvcDeadheadProp	100%	100%
ShdCarSvcDeadheadFactor	100%	100%
UnShdCarSvcDeadheadFactor	100%	100%

Data valid as of 10.30.25

azone_charging_availability.csv

Category: Vehicle & Fuels

This input file specifies the share of different housing types that have sufficient home-based charging to support privately owned electric vehicles or have potential to host charging infrastructure. This could also include readily available curb-based charging for parking spaces available to residents. This input does not include public chargers that would require higher costs to use like DC Fast Chargers (DCFCs). The data is entered by housing type for each of the Azones in the model region. The input file uses a numeric value between 0 and 1 to represent the share of the households with home charging access by dwelling unit type (single family, multifamily, or group quarters unit). Data for San Joaquin Valley Azones were determined using the California Mandatory Electric Vehicle Building Standards and were assumed to be 100% availability for single family homes, 40% for multifamily, and 15% for group quarters.[7]

TABLE 5: CHARGING AVAILABILITY SUMMARY

YEAR	PROPSFCHARGINGAVAIL	PROPMFCHARGINGAVAIL	PROPGQCHARGINGAVAIL
2022	100%	40%	15%
2046	100%	40%	15%

Data valid as of 10.30.25

azone_electricity_carbon_intensity.csv

Category: Vehicle & Fuels

This input file specifies the carbon intensity of electricity at the point of consumption in grams CO2e per megajoule by Azone. This input uses 2022 annual power content labels reported by utility companies to the California Energy Commission. Carbon intensity values were converted to grams of CO2e per megajoule. Each Azone was assigned a carbon intensity value of the utility company that operated in its area. If multiple providers operated in the same Azone, an average value was calculated. 2046 values are equal to zero as California mandates that the state shall rely 100% on clean electricity by 2045.

TABLE 6: CARBON INTENSITY SUMMARY

MAREA	YEAR	ELECTRICITY.CI
FCOG	2022	15.3
FCOG	2046	0.0
KCOG	2022	48.3
KCOG	2046	0.0
KCAG	2022	39.6
KCAG	2046	0.0
MCAG	2022	47.7
MCAG	2046	0.0
MCTC	2022	11.2
MCTC	2046	0.0
SJCOG	2022	30.8
SJCOG	2046	0.0
StanCOG	2022	47.1

[7] https://afdc.energy.gov/laws/11068#:~:text=New%20one-%20and%20two-unit,with%20Level%202%20EV%20chargers.&text=In%20cases%20in%20which%20EV,requirements%2C%20see%20the%20CBSC%20website.&text=See%20all%20California%20Laws%20and%20Incentives.

MAREA	YEAR	ELECTRICITY.CI
StanCOG	2046	0.0
TCAG	2022	56.5
TCAG	2046	0.0

Data valid as of 10.30.25

azone_fuel_power_cost.csv

Category: Setup

This input provides data for the cost of liquid and electricity fuel minus any taxes by Azone. This includes the retail cost of fuel per gas gallon equivalent and retail cost of electricity per kilowatt-hour minus any applicable federal, state, and local taxes. Base year power costs per county were obtained from Find Energy[8] and retail fuel costs per county were obtained from AAA[9] and adjusted to reflect the cost of fuel by removing federal, state, and county taxes. Both gas and electricity costs were collected from 2025 data for the base year. Azones were assigned the costs of the county they belong to. No change is assumed between 2022 and 2046 cost values in real terms.

TABLE 7: FUEL POWER COST SUMMARY

MAREA	YEAR	POWERCOST.2022	FUELCOST.2022
FCOG	2022	$ 0.39	$ 3.49
FCOG	2046	$ 0.39	$ 3.49
KCOG	2022	$ 0.35	$ 3.47
KCOG	2046	$ 0.35	$ 3.47
KCAG	2022	$ 0.39	$ 3.34
KCAG	2046	$ 0.39	$ 3.34
MCAG	2022	$ 0.37	$ 3.38
MCAG	2046	$ 0.37	$ 3.38
MCTC	2022	$ 0.40	$ 3.48
MCTC	2046	$ 0.40	$ 3.48
SJCOG	2022	$ 0.38	$ 3.38
SJCOG	2046	$ 0.38	$ 3.38
StanCOG	2022	$ 0.25	$ 3.27
StanCOG	2046	$ 0.25	$ 3.27
TCAG	2022	$ 0.33	$ 3.42
TCAG	2046	$ 0.33	$ 3.42

Data valid as of 10.30.25

[8] https://findenergy.com/ca/#ca-counties
[9] https://gasprices.aaa.com/?state=CA

azone_gq_pop_by_age.csv

Category: Demographics

This input provides group quarters population estimates by the following age bins:

- Age 0-14
- Age 15-19
- Age 20-29
- Age 30-54
- Age 55-64
- Age 65 plus

These estimates use only non-institutional group quarters populations, which include individuals living in college dormitories, military barracks, group homes, missions, or shelters. Those living in institutional group quarters, such as correctional facilities or nursing homes, are not included. Both the FCOG and MCTC travel models and synthetic population data provided estimates of group quarters residents. Census estimates for 2022 were used to inform estimates for KCAG, KCOG, MCAG, SJCOG, StanCOG, and TCAG.[10,11,12,13,14,15] GQ population was assigned to Azones containing non-institutional group quarters facilities, such as universities or military barracks.

TABLE 8: GROUP QUARTERS POPULATION SUMMARY

MAREA	YEAR	AGE0TO14	AGE15TO19	AGE20TO29	AGE30TO54	AGE55TO64	AGE65PLUS
FCOG	2022	0	1,423	1,732	1,862	686	1,297
FCOG	2046	0	2,041	2,074	2,025	652	1,188
KCOG	2022	0	2,023	2,462	0	0	0
KCOG	2046	0	2,224	2,261	0	0	0

10 https://dof.ca.gov/media/docs/forecasting/Demographics/2020-census-data/2020Census_PL942020_Profile_Calif_Kings.pdf
11 https://dof.ca.gov/media/docs/forecasting/Demographics/2020-census-data/2020Census_PL942020_Profile_Calif_Kern.pdf
12 https://dof.ca.gov/media/docs/forecasting/Demographics/2020-census-data/2020Census_PL942020_Profile_Calif_Merced.pdf
13 https://dof.ca.gov/media/docs/forecasting/Demographics/2020-census-data/2020Census_PL942020_Profile_Calif_San-Joaquin.pdf
14 https://dof.ca.gov/media/docs/forecasting/Demographics/2020-census-data/2020Census_PL942020_Profile_Calif_Stanislaus.pdf
15 https://dof.ca.gov/media/docs/forecasting/Demographics/2020-census-data/2020Census_PL942020_Profile_Calif_Tulare.pdf

KCAG	2022	0	650	789	0	0	0
KCAG	2046	0	713	726	0	0	0
MCAG	2022	0	1,290	1,572	0	0	0
MCAG	2046	0	1,420	1,442	0	0	0
MCTC	2022	0	289	350	0	0	0
MCTC	2046	0	316	323	0	0	0
SJCOG	2022	0	3,676	4,475	0	0	0
SJCOG	2046	0	4,042	4,109	0	0	0
StanCOG	2022	0	1,791	2,181	0	0	0
StanCOG	2046	0	1,970	2,002	0	0	0
TCAG	2022	0	1,117	1,359	0	0	0
TCAG	2046	0	1,226	1,250	0	0	0

Data valid as of 11.25.25

azone_hh_lttrk_prop.csv

Category: Vehicle & Fuels

This file specifies the proportion of household vehicles that are light trucks. This input uses 2022 registered vehicle data by county provided by the California DMV. The proportion of trucks includes commercial and non-commercial trucks. No change is assumed from 2022 to 2046.

TABLE 9: LIGHT TRUCK PROPORTION SUMMARY

MAREA	YEAR	LTTRKPROP
FCOG	2022	22.9%
FCOG	2046	22.9%
KCOG	2022	25.1%
KCOG	2046	25.1%
KCAG	2022	23.8%
KCAG	2046	23.8%
MCAG	2022	23.8%
MCAG	2046	23.8%
MCTC	2022	24.2%
MCTC	2046	24.2%
SJCOG	2022	20.4%
SJCOG	2046	20.4%
StanCOG	2022	22.7%
StanCOG	2046	22.7%
TCAG	2022	25.4%
TCAG	2046	25.4%

Data valid as of 10.30.25

azone_hh_pop_by_age.csv

Category: Demographics

This file contains household population estimates by age. The age bins are:

- Age 0-14
- Age 15-19
- Age 20-29
- Age 30-54
- Age 55-64
- Age 65 Plus

Populations for all model years are calculated using a combination of MPO travel model data, MPO population forecasts, and ACS data for the base model year. MPO data is developed with the following methodologies:

- FCOG data was developed using synthetic population and household data provided by FCOG.
- KCOG, SJCOG, and TCAG Mareas use the MPO provided TAZ socioeconomic data for each model year to create a distribution of population, then applied population forecast data for each model year.[16, 17, 18]
- MCAG uses American Community Survey (ACS) 2022 data to develop age bin distributions by Bzone and then applies MCAG population forecast data for 2022 and 2046.
- KCAG, MCTC, and StanCOG data were developed directly from the TAZ socioeconomic data provided by the MPOs.

TABLE 10: HOUSEHOLD POPULATION BY AGE AND MAREA

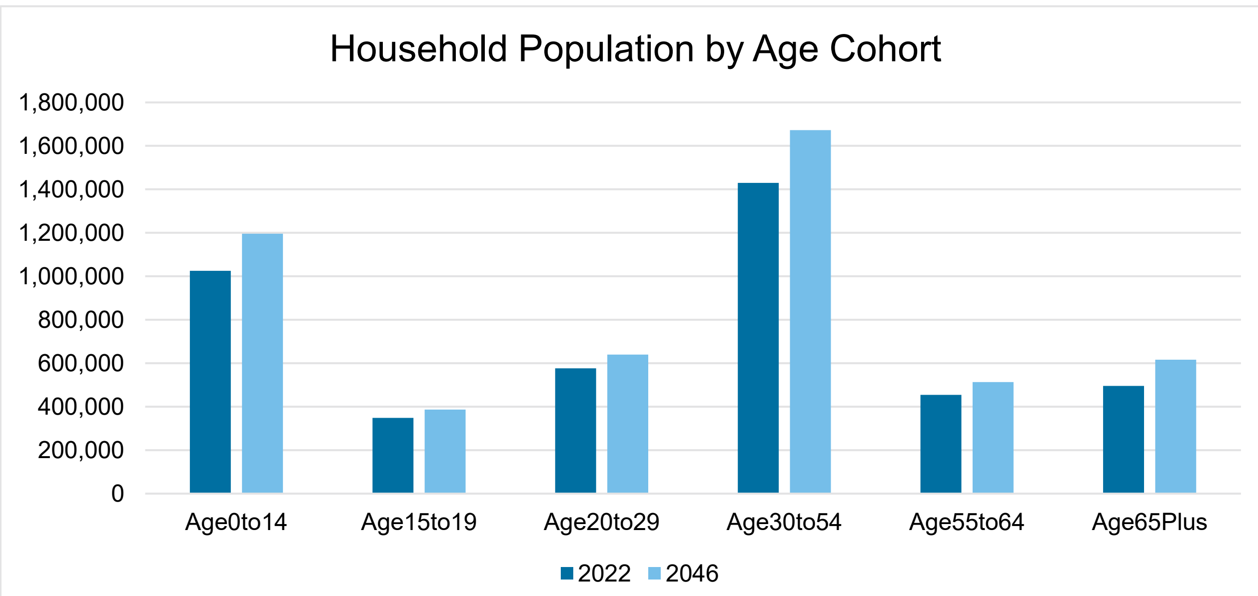
MAREA	YEAR	0-14	15-19	20-29	30-54	55-64	65+	TOTAL
FCOG	2022	264,080	73,234	160,806	317,102	106,069	125,719	1,047,010
	2046	309,823	77,745	172,213	365,702	122,725	141,506	1,189,714
KCOG	2022	196,540	72,366	114,998	312,785	93,902	93,081	883,672
	2046	214,046	68,505	112,724	352,812	89,633	149,442	987,162

[16] https://www.kerncog.org/wp-content/uploads/2024/06/Growth_Forecast_2024_2050.pdf
[17] https://www.sjcog.org/DocumentCenter/View/7085/Q-Population-Household-and-Employment-Projections
[18] https://tularecog.org/tcag/planning/rtp/rtp-2022/appendices

KCAG	2022	29,040	11,980	17,654	48,137	10,213	13,879	130,903
	2046	32,618	13,560	20,235	55,540	11,408	16,398	149,759
MCAG	2022	69,030	24,915	42,734	88,675	29,641	33,536	288,531
	2046	79,412	28,660	49,160	102,004	34,098	38,577	331,911
MCTC	2022	35,834	12,702	17,939	50,683	18,208	18,678	154,044
	2046	43,160	16,037	23,240	64,443	25,482	25,129	197,491
SJCOG	2022	181,649	65,040	95,350	265,567	86,173	90,646	784,425
	2046	221,063	78,168	112,151	319,917	100,768	105,177	937,244
StanCOG	2022	125,042	46,661	68,582	189,784	61,311	66,907	558,287
	2046	150,173	56,032	82,364	227,930	73,634	80,357	670,490
TCAG	2022	123,406	41,891	58,557	157,515	48,639	53,365	483,373
	2046	144,985	48,544	67,864	184,677	55,008	60,201	561,279

Data valid as of 11.6.25

FIGURE 10: HOUSEHOLD POPULATION BY AGE COHORT



azone_hh_veh_mean_age.csv

Category: Vehicles & Fuels

This input provides the mean age for household autos and light trucks. This input was developed using 2022 DMV vehicle registration data, filtered by ZIP codes within the San Joaquin Valley model region. No change was assumed between model years.

TABLE 11: AVERAGE VEHICLE AGE BY VEHICLE TYPE

MAREA	YEAR	AUTOMEANAGE	LTTRKMEANAGE
FCOG	2022	8.3	8.3
FCOG	2046	8.3	8.3
KCOG	2022	8.2	8.2
KCOG	2046	8.2	8.2
KCAG	2022	8.3	8.3
KCAG	2046	8.3	8.3
MCAG	2022	8.4	8.4
MCAG	2046	8.4	8.4
MCTC	2022	8.3	8.3
MCTC	2046	8.3	8.3
SJCOG	2022	8.1	8.1
SJCOG	2046	8.1	8.1
StanCOG	2022	8.3	8.3
StanCOG	2046	8.3	8.3
TCAG	2022	8.4	8.4
TCAG	2046	8.4	8.4

Data valid as of 10.30.25

azone_hh_veh_own_taxes.csv

Category: Pricing

This input indicates flat fees and taxes in annual cost per vehicle and ad valorem taxes. Data for base year fees were obtained from the 2025 California DMV fee tables and the DMV vehicle registration fee calculator. Fees were obtained at the county level and applied to Azones based on their county. No changes in real terms were assumed for 2046.

TABLE 12: VEHICLE OWNERSHIP TAXES SUMMARY

MAREA	YEAR	VEHOWNFLATRATEFEE.2022	VEHOWNADVALOREMTAX
FCOG	2022	$253.00	$0.65
FCOG	2046	$253.00	$0.65
KCOG	2022	$255.00	$0.65
KCOG	2046	$255.00	$0.65
KCAG	2022	$255.00	$0.65
KCAG	2046	$255.00	$0.65
MCAG	2022	$256.00	$0.65
MCAG	2046	$256.00	$0.65
MCTC	2022	$254.00	$0.65

MCTC	2046	$254.00	$0.65
SJCOG	2022	$255.00	$0.65
SJCOG	2046	$255.00	$0.65
StanCOG	2022	$254.00	$0.65
StanCOG	2046	$254.00	$0.65
TCAG	2022	$254.00	$0.65
TCAG	2046	$254.00	$0.65

Data valid as of 10.30.25

azone_hhsize_targets.csv

Category: Demographics

This input contains household size targets for the population synthesizer. The two attributes are average non-group quarters household size and proportion of non-group quarters households containing only one person. The input data for each MPO was developed with the following methodologies:

- FCOG used the synthetic household and population data provided by that MPO to determine the average household size and the number of single-person households.
- KCOG, KCAG, MCTC, SJCOG, StanCOG, and TCAG used the MPO-provided TAZ socioeconomic data to determine the average household size and single-person households.
- MCAG used ACS 2022 data to determine the proportion of single-person households by Azone, and used the bzone_dwelling_units input and azone_hh_pop_by_age input to calculate the average household size.

TABLE 13: HOUSEHOLD SIZE TARGETS BY YEAR AND AZONE

MAREA	YEAR	AVEHHSIZE	PROP1PERHH
FCOG	2022	3.10	22%
FCOG	2046	3.11	21%
KCOG	2022	3.06	17%
KCOG	2046	2.63	16%
KCAG	2022	2.88	14%
KCAG	2046	2.89	14%
MCAG	2022	3.34	11%
MCAG	2046	3.19	11%
MCTC	2022	3.06	15%
MCTC	2046	3.07	15%
SJCOG	2022	3.15	19%

SJCOG	2046	3.10	19%
StanCOG	2022	3.17	18%
StanCOG	2046	3.17	18%
TCAG	2022	3.14	15%
TCAG	2046	2.95	16%

Date: valid as of 11.21.25

azone_payd_insurance_prop.csv

Category: Pricing

This file provides information on the proportion of households that use pay-as-you-drive insurance. Pay-as-you-drive (PAYD) insurance allows drivers to pay insurance fees based on the number of miles driven. The lower the number of miles driven, the lower the insurance cost.

This input assumes no drivers in the model region will use PAYD insurance.

TABLE 14: PAY AS YOU DRIVE INSURANCE SUMMARY

YEAR	PAYDHHPROP
2022	0.0%
2046	0.0%

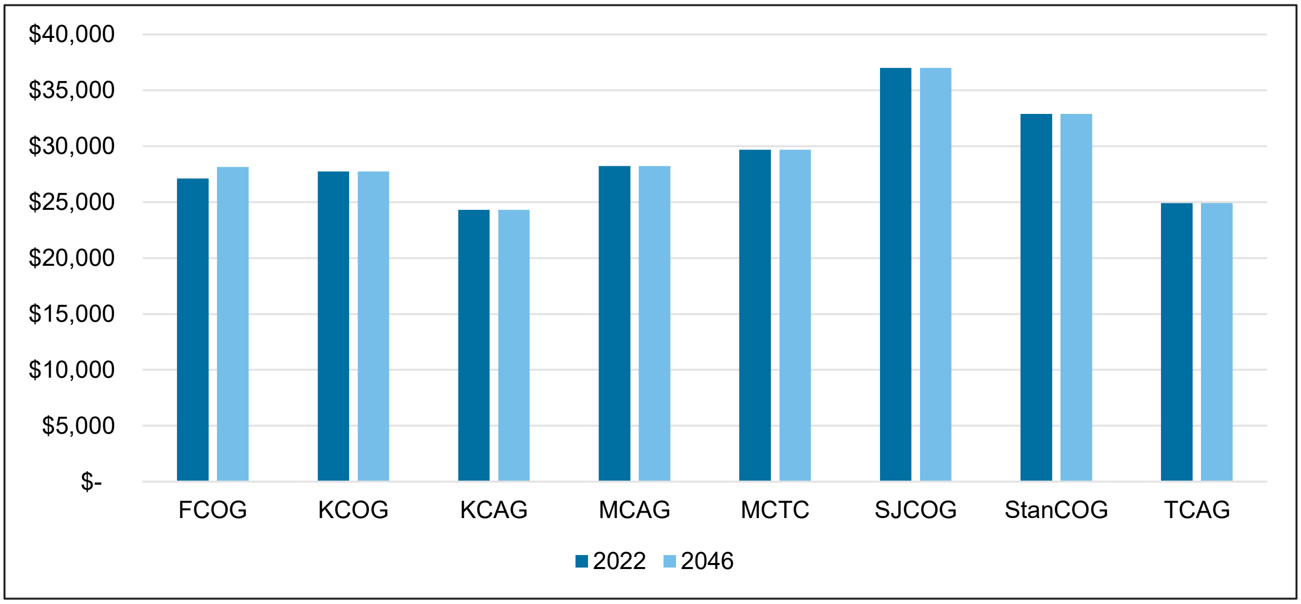
Date: valid as of 10.30.25

azone_per_cap_inc.csv

Category: Demographics

This file provides the regional per capita income for household and group quarters residents in 2019 dollars. Incomes for the San Joaquin Valley model region were calculated using a combination of TAZ socioeconomic data and ACS 2022 data. FCOG estimates were calculated using synthetic population and household data provided by FCOG, while incomes for other MPOs were estimated from ACS 2022 data. No growth was assumed for MPOs that used ACS data. Group quarters income was calculated as $10,000 a year for group quarters population aged less than 20 years old, and $15,000 a year for group quarters population aged over 20 years old. As the figure below shows, the only subarea in which this approach assumes future real income growth is FCOG's planning geography.

FIGURE 11: HOUSEHOLD PER CAPITA INCOME BY MAREA (2022$)



Date: valid as of 10.30.25

TABLE 15: REGIONAL SUMMARY OF PER CAPITA INCOME

YEAR	REGIONAL AVERAGE PER CAPITA INCOME (2022$)	REGIONAL AVERAGE GROUP QUARTER PER CAPITA INCOME (2022$)
2022	$29,815	$ 4,346
2046	$30,012	$4,345

Date: valid as of 11.26.25

azone_prop_sov_dvmt_diverted.csv

Category: Transportation Options

In VisionEval, bike trips, along with trips taken by any personal lightweight mode, are represented through the diversion of eligible household single occupancy vehicle (SOV) trips (for 20-mile or less tour distances). Personal lightweight modes refer to an evolving class of vehicles encompassing bicycles (both pedal-powered and electric), standing and seated electric scooters (e-scooters), electric skateboards, and other slow speed modes designed for a single user. The input file provides goals for the proportion of eligible household SOV daily vehicle miles traveled (DVMT) to be diverted to bicycling or other personal modes at the Azone level. The input value is a value between 0 and 1 to reflect the percentage of eligible trips (0 to 100%). VisionEval has a sub-model that estimates the number of trips that meet this 20-mile threshold and then uses this input to divert some of those trips from the vehicle model to active modes.

This input is a key input to model walking and biking trips and is used to further shift trips away from vehicles as walking and biking infrastructure improvements are made.

This input was estimated using data from the 2023 San Joaquin Valley Household Travel Survey, which contained estimates of the number active transportation mode trips versus vehicle trips by 2010 PUMA. Rates of active travel were applied to respective Azones and compared to the 2019 and 2022 Census Journey to Work data for validation. No changes were assumed for future model years.

TABLE 16: SOV DIVERSION INPUT BY AZONE

MAREA	YEAR	PROPSOVDVMTDIVERTED
FCOG	2022	1.19%
FCOG	2046	1.19%
KCOG	2022	0.87%
KCOG	2046	0.87%
KCAG	2022	0.60%
KCAG	2046	0.60%
MCAG	2022	0.71%
MCAG	2046	0.71%
MCTC	2022	0.30%
MCTC	2046	0.30%
SJCOG	2022	1.24%
SJCOG	2046	1.24%
StanCOG	2022	1.18%
StanCOG	2046	1.18%
TCAG	2022	0.48%
TCAG	2046	0.48%

Date: valid as of 10.30.25

The regional average by year is shown in Table 17~~Table 17~~.

TABLE 17: SOV DIVERSION INPUT REGIONAL AVERAGE

YEAR	PROPSOVDVMTDIVERTED
2022	0.8%
2046	0.8%

Date: valid as of 10.30.2025

azone_relative_employment.csv

Category: Setup

Policy: Demographics

Authority: Local

This input contains the ratio of workers to total population within an Azone by age. The age bins are divided into:

- Age 15-19
- Age 20-29
- Age 30-54
- Age 55-64
- Age 65 Plus

The input uses a value of 1 for all brackets. This value was derived through robust statewide testing to align the number of workers with the number of jobs in the state.

Note that the SJV-VE model has an economic boundary, that the employment numbers in the model are derived from the regional travel demand models' inputs, and that employment locations within the Valley may attract workers from outside of the model region. This input factor simply ensures that across the entire state all regional models are consistent with the statewide model, but it is anticipated that within any region, there will be a difference between the number of workers and the number of jobs (e.g., employment) in the model.

azone_veh_use_taxes.csv

Category: Pricing

This input file accounts for various fuel taxes and road use charges that may be imposed upon vehicles. The input file includes 2025 federal and state gasoline taxes, along with county-specific fuel taxes. The total tax was obtained at the county level and applied to Azones based on their county location. California agencies do not impose additional VMT taxes. No changes in taxes were assumed for 2046.

TABLE 18: VEHICLE USE TAXES

MAREA	YEAR	FUELTAX.2022	VMTTAX.2022	PERSURCHGTAXPROP
FCOG	2022	$0.88	$0.00	$0.00
FCOG	2046	$0.88	$0.00	$0.00
KCOG	2022	$0.87	$0.00	$0.00
KCOG	2046	$0.87	$0.00	$0.00
KCAG	2022	$0.87	$0.00	$0.00
KCAG	2046	$0.87	$0.00	$0.00
MCAG	2022	$0.87	$0.00	$0.00
MCAG	2046	$0.87	$0.00	$0.00
MCTC	2022	$0.87	$0.00	$0.00
MCTC	2046	$0.87	$0.00	$0.00

SJCOG	2022	$0.87	$0.00	$0.00
SJCOG	2046	$0.87	$0.00	$0.00
StanCOG	2022	$0.87	$0.00	$0.00
StanCOG	2046	$0.87	$0.00	$0.00
TCAG	2022	$0.87	$0.00	$0.00
TCAG	2046	$0.87	$0.00	$0.00

Date: valid as of 10.30.25

azone_vehicle_access_times.csv

Category: Transportation Options

This file accounts for the accessibility of car sharing or ride hailing compared to the private vehicle. For some locations, especially in urban areas, it is sometimes more convenient to use an on-demand vehicle instead of walking to a parking garage to access one's own vehicle. For each Azone in the model region, the input identifies how many minutes are required to access (either to or from) the vehicle for the following situations:

- Typical time to access the vehicle(s) owned by the household.
- Typical time to access a high service ride hailing vehicle (Uber and Lyft).
- Typical time to access low service car sharing service (station based or free floating).

The San Joaquin Valley model uses default VisionEval values for this input.

TABLE 19: VEHICLE ACCESS TIMES

YEAR	OWNEDVEHACCESSTIME	HIGHCARSVCACCESSTIME	LOWCARSVCACCESSTIME	SHDCARSVCACCESSTIME	UNSHDCARSVCACCESSTIME
2022	2	10	10	10	10
2046	2	10	10	10	10

Date: Valid as of 10.30.25

azone_wkr_loc_type_occupation_prop.csv

Category: Demographics

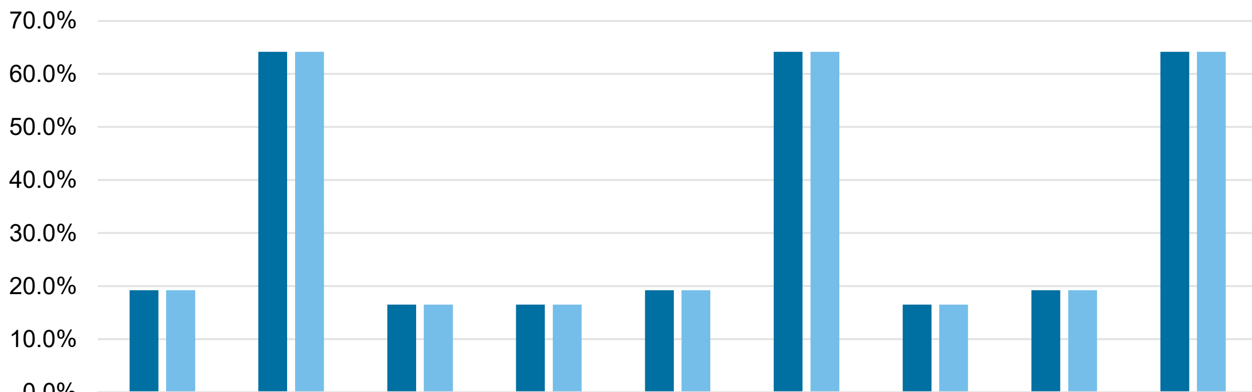
This input estimates the proportions for workers residing in an Azone that work in either metropolitan, town, or rural areas of the Azone. This input was developed using Bureau of Labor Statistics Standard Occupational Classification (SOC) estimates. No changes were assumed between model years.

TABLE 20: WORKER AND LOCATION TYPE PROPORTIONS

					2022			
VARIABLE	FCOG	KCAG	KCOG	MCAG	MCTC	SJCOG	STANCOG	TCAG
PropRuralMixed	18.7%	23.6%	18.1%	18.4%	17.5%	22.3%	18.8%	16.7%
PropRuralOnSite	62.6%	62.1%	64.3%	66.4%	68.5%	56.4%	64.5%	68.7%
PropRuralRemote	18.7%	14.4%	17.5%	15.1%	14.0%	21.3%	16.6%	14.6%
PropTownRemote	18.7%	14.4%	17.5%	15.1%	14.0%	21.3%	16.6%	14.6%
PropTownMixed	18.7%	23.6%	18.1%	18.4%	17.5%	22.3%	18.8%	16.7%
PropTownOnSite	62.6%	62.1%	64.3%	66.4%	68.5%	56.4%	64.5%	68.7%
PropMetroRemote	18.7%	14.4%	17.5%	15.1%	14.0%	21.3%	16.6%	14.6%
PropMetroMixed	18.7%	23.6%	18.1%	18.4%	17.5%	22.3%	18.8%	16.7%
PropMetroOnSite	62.6%	62.1%	64.3%	66.4%	68.5%	56.4%	64.5%	68.7%
					2046			
VARIABLE	FCOG	KCAG	KCOG	MCAG	MCTC	SJCOG	STANCOG	TCAG
PropRuralMixed	18.7%	23.6%	18.1%	18.4%	17.5%	22.3%	18.8%	16.7%
PropRuralOnSite	62.6%	62.1%	64.3%	66.4%	68.5%	56.4%	64.5%	68.7%
PropRuralRemote	18.7%	14.4%	17.5%	15.1%	14.0%	21.3%	16.6%	14.6%
PropTownRemote	18.7%	14.4%	17.5%	15.1%	14.0%	21.3%	16.6%	14.6%
PropTownMixed	18.7%	23.6%	18.1%	18.4%	17.5%	22.3%	18.8%	16.7%
PropTownOnSite	62.6%	62.1%	64.3%	66.4%	68.5%	56.4%	64.5%	68.7%
PropMetroRemote	18.7%	14.4%	17.5%	15.1%	14.0%	21.3%	16.6%	14.6%
PropMetroMixed	18.7%	23.6%	18.1%	18.4%	17.5%	22.3%	18.8%	16.7%
PropMetroOnSite	62.6%	62.1%	64.3%	66.4%	68.5%	56.4%	64.5%	68.7%

Data valid as of 10.30.25

FIGURE 12: WORKER TELEWORKING OCCUPATION CATEGORY



	PropRural Mixed	PropRural OnSite	PropRural Remote	PropTown Remote	PropTown Mixed	PropTown OnSite	PropMetro Remote	PropMetro Mixed	PropMetro OnSite
2022	19.3%	64.2%	16.5%	16.5%	19.3%	64.2%	16.5%	19.3%	64.2%
2046	19.3%	64.2%	16.5%	16.5%	19.3%	64.2%	16.5%	19.3%	64.2%

Data valid as of 10.30.25

bzone_carsvc_availability.csv

Category: Transportation Options

This input file contains the information about level of car service (car sharing or ride hailing) availability and contains a value of either “Low” or “High” for all Bzones. High means car service access is competitive with household owned cars and could impact household vehicle ownership. Low car service is considered not competitive enough to affect household vehicle ownership. Either car service will attract some demand from a house and will reduce travel on any vehicles owned by the household. Each of the Bzones needs to be considered as to whether car sharing services are available and tagged with either “Low” coverage, or if the Bzone has decent coverage by ride hailing vehicles (a is a subjective decision) then the Bzone is classified as “High”. The input file, azone_carsvc_characteristics.csv, includes the related time to access the car sharing and ride hailing.

This input was calculated using the San Joaquin Valley Household Travel Survey data, which includes information on ride-hailing trips. Bzones in the 70th percentile or higher of proportion of trips attributed to ride-hailing were assigned a high level of car service and shared car service. No changes were assumed for the future year.

TABLE 21: SUMMARY OF CAR SERVICE LEVELS (NUMBER OF BZONES)

	CARSVCLEVEL		SHDSVCAVAIL	
Year	Low	High	No	Yes
2019	1,927	819	1,927	819
2050	1,927	819	1,927	819

Data valid as of 9.10.25

bzone_dwelling_units.csv

Category: Land use

This file contains the number of dwelling units by type and Bzone. Dwelling unit types include single-family (SF) housing, multi-family (MF) housing, and non-institutional group quarters (e.g. university housing, military barracks). Travel model data was used to calculate total dwelling units by type for FCOG, KCAG, MCAG, MCTC, and StanCOG. Travel model data was used as a distribution of households by type for KCOG, SJCOG, and TCAG, and official household forecast numbers were applied to the distribution.[19, 20, 21]

Group quarters population was summarized using either group quarters data available in the travel model data or ACS data by county (see sources in azone_gq_pop_by_age input) and were cross-referenced with university and military barracks locations. One group quarters dwelling unit was assumed per group quarters population.

TABLE 22: DWELLING UNITS SUMMARY

MAREA	YEAR	SFDU	MFDU	GQDU	TOTAL (SFDU + MFDU)
FCOG	2022	242,547	85,019	7,006	327,566
FCOG	2046	265,819	107,918	7,986	373,737
KCOG	2022	230,401	51,657	4,485	282,058
KCOG	2046	276,766	71,027	4,485	347,793
KCAG	2022	34,647	8,931	1,439	43,578
KCAG	2046	40,087	9,991	1,439	50,078
MCAG	2022	74,399	13,105	2,862	87,504
MCAG	2046	88,513	25,596	2,862	114,109
MCTC	2022	42,708	6,559	639	49,267
MCTC	2046	53,094	10,204	639	63,298
SJCOG	2022	195,968	52,436	8,151	248,404

[19] https://www.kerncog.org/wp-content/uploads/2024/06/Growth_Forecast_2024_2050.pdf
[20] https://www.sjcog.org/DocumentCenter/View/7085/Q-Population-Household-and-Employment-Projections
[21] https://tularecog.org/tcag/planning/rtp/rtp-2022/appendices

SJCOG	2046	225,224	79,920	8,151	305,144
StanCOG	2022	141,402	41,056	3,972	182,458
StanCOG	2046	173,785	50,380	3,972	224,165
TCAG	2022	122,623	34,565	2,476	157,188
TCAG	2046	139,206	56,179	2,476	195,385

Data valid as of 11.25.25

bzone_employment.csv

Category: Land use

This input contains data on the total number of employees in each Bzone and is further broken into the number of employees in service and retail sectors. MCAG and MCTC employment is directly calculated from TAZ socioeconomic data. RSG created distributions of employment using TAZ data for FCOG, KCOG, KCAG, SJCOG, StanCOG, and TCAG, then applied the distribution to the officially forecasted employment totals for each MPO to create the broken out numbers shown in the table below.[22, 23, 24, 25, 26, 27]

The distributions of retail and service employment were calculated by block group using LEHD data for the model region, then crosswalked and applied to total employment within a Bzone.

TABLE 23: EMPLOYMENT SUMMARY

MAREA	YEAR	TOTEMP	RETEMP	SVCEMP
FCOG	2022	414,758	37,575	172,749
FCOG	2046	466,148	42,229	193,539
KCOG	2022	347,303	33,378	117,079
KCOG	2046	417,692	39,201	144,980
KCAG	2022	57,200	5,298	8,607
KCAG	2046	65,380	5,955	10,586
MCAG	2022	86,883	18,642	32,950
MCAG	2046	103,300	21,965	40,411
MCTC	2022	51,298	4,223	10,742

[22] https://www.fresnocog.org/wp-content/uploads/2023/11/2024-Fresno-COG-2023-2060-Growth-Projections-adopted-Nov_21_2024.pdf
[23] https://www.kerncog.org/wp-content/uploads/2024/06/Growth_Forecast_2024_2050.pdf
[24] https://www.countyofkingsca.gov/departments/general-services/jto-edc/kings-county-economic-development-corporation/county-facts/demographics
[25] https://www.sjcog.org/DocumentCenter/View/7085/Q-Population-Household-and-Employment-Projections
[26] https://www.stancog.org/DocumentCenter/View/178/2021-Stanislaus-County-Demographic-and-Employment-Forecast-PDF?bidId=
[27] https://tularecog.org/tcag/planning/rtp/rtp-2022/appendices

MCTC	2046	65,143	5,638	14,345
SJCOG	2022	364,059	39,730	129,894
SJCOG	2046	414,671	40,183	166,050
StanCOG	2022	256,138	31,488	97,742
StanCOG	2046	295,925	36,395	112,937
TCAG	2022	188,437	19,599	47,920
TCAG	2046	218,819	23,262	59,756

Data valid as of 11.6.25

Values for the external zones mirror the commuter flows to counties outside the model region in the LEHD initial analysis. These were not changed between model years.

TABLE 24: EXTERNAL ZONES EMPLOYMENT

MAREA	2022	2046
Alameda	60,477	60,477
Amador	635	635
Calaveras	1,031	1,031
ContraCosta	20,411	20,411
Inyo	396	396
LosAngeles	59,258	59,258
Mariposa	1,033	1,033
Mono	288	288
Monterey	8,592	8,592
Sacramento	30,774	30,774
SanBenito	1,453	1,453
SanBernardino	15,400	15,400
SanLuisObispo	4,977	4,977
SantaBarbara	6,022	6,022
SantaClara	47,023	47,023
Tuolumne	1,654	1,654
Ventura	7,135	7,135

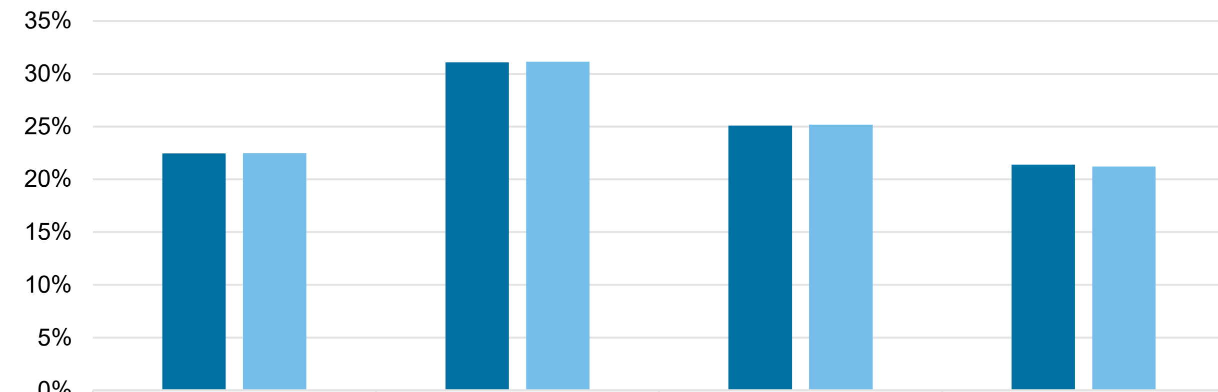
Data valid as of 11.6.25

bzone_hh_inc_qrtl_prop.csv

Category: Land use

This input contains the proportion of Bzone non-group quarter households by quartile of Azone household income category. This input was estimated using the quartile breaks of family income and number of households in 2022 ACS data by Azone, then applied to households residing within the Azone.

FIGURE 13: HOUSEHOLD PROPORTION BY INCOME QUARTILES



	HhPropIncQ1	HhPropIncQ2	HhPropIncQ3	HhPropIncQ4
2022	22%	31%	25%	21%
2046	22%	31%	25%	21%

Data valid as of 9.29.25

bzone_lat_lon.csv

This file contains the longitude and latitude of the centroid of each Bzone.

bzone_network_design.csv

Category: Land use

This input contains the EPA Smart Location Database (SLD) measure for intersection density (D3bpo4), specifically pedestrian-oriented intersections with four or more legs per square mile. The San Joaquin Valley model uses the weighted average of joined SLD values for each Bzone. The inputs assume no change between the base and future years.

TABLE 25: PEDESTRIAN FRIENDLY INTERSECTION DENSITY AVERAGES

MAREA	2022	2046
FCOG	17.1	17.1
KCOG	13.4	13.4
KCAG	21.3	21.3
MCAG	19.0	19.0
MCTC	19.1	19.1
SJCOG	22.7	22.7
StanCOG	19.3	19.3

TCAG	17.3	17.3

Data valid as of 9.9.25

bzone_parking.csv

Category: Land use

This file contains a range of parking information by Bzone for each of the model years. This file was calculated using paid parking locations provided by each MPO and research on paid parking locations within each MPO area, including both on and off-street parking locations and rates. These were converted into maximum daily parking costs in 2022 USD.

The input file accounts for the following components:

- Number of free parking spaces available to residents by dwelling unit type (single family, multi family, and group quarters).
- Proportion of workers that pay for parking, both in and not in a cash-out buyback program. Cash-out buyback is a travel demand management / travel options program where employers who offer parking to staff as a benefit, offer to pay workers who do not use that benefit the cash value of that parking.
- Average daily cost for long-term parking.

MPOs provided either locations of paid parking or feedback on where paid parking may be located. While limited, paid parking locations throughout the model region generally include universities and some paid parking in downtown areas. Most MPOs had little or no paid parking. Estimates for proportions of work trips that required paid parking were provided by Fresno COG. It was assumed that all non-work trips in university Bzones with parking costs will require paid parking, and half of all non-work trips in non-university Bzones with parking costs will require paid parking. No changes were made between model years.

TABLE 26: PARKING SUMMARY

	2022							
	FCOG	**KCOG**	**KCAG**	**MCAG**	**MCTC**	**SJCOG**	**STANCOG**	**TCAG**
PkgSpacesPerSFDU	4	4	4	4	4	4	4	4
PkgSpacesPerMFDU	2	2	2	2	2	2	2	2
PkgSpacesPerGQ	0	0	0	0	0	0	0	0
PropCashOut	0	0	0	0	0	0	0	0
PropWkrPay	5.3%	0.4%	9.7%	8.1%	5.9%	7.9%	6.6%	8.5%
PropNonWrkTripPay	1.3%	0.4%	0.0%	0.0%	0.0%	0.5%	0.1%	0.1%
PkgCost.2022	$0.13	$0.02	$0.00	$0.00	$0.00	$0.07	$0.02	$0.00

	2046							
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
PkgSpacesPerSFDU	4	4	4	4	4	4	4	4
PkgSpacesPerMFDU	2	2	2	2	2	2	2	2
PkgSpacesPerGQ	0	0	0	0	0	0	0	0
PropCashOut	0	0	0	0	0	0	0	0
PropWkrPay	5.3%	0.4%	9.7%	8.1%	5.9%	7.9%	6.6%	8.5%
PropNonWrkTripPay	1.3%	0.4%	0.0%	0.0%	0.0%	0.5%	0.1%	0.1%
PkgCost.2022	$0.13	$0.02	$0.00	$0.00	$0.00	$0.07	$0.02	$0.00

Data valid as of 9.29.25

bzone_transit_service.csv

Category: Transportation options

This input contains information on public transportation accessibility using the D4c variable from the EPA Smart Location Database (SLD). This variable represents the frequency of transit service within 0.25 miles of a block group boundary during the evening peak period. The buffered travel routes from GTFS feeds provided by each MPO were used to estimate aggregate stop frequencies by Bzone. No future change was assumed for the model region.

TABLE 27: TRANSPORTATION ACCESSIBILITY (D4C) SUMMARY

MAREA	2022	2046
FCOG	31.5	31.5
KCOG	10.8	10.8
KCAG	13.0	13.0
MCAG	11.6	11.6
MCTC	5.8	5.8
SJCOG	13.1	13.1
StanCOG	26.5	26.5
TCAG	4.9	4.9

Data valid as of 9.11.25

bzone_travel_demand_mgt.csv

Category: Transportation options

This file contains information about the share of workers and households participating in travel demand management (TDM) programs or who might be members of a transportation management association (TMA). Ideally, agencies would collect information from organizations that offer travel options programs. Local jurisdictions provided some custom TDM data required for this input. The inputs are a value between 0 and 1 for each Bzone (0% to 100%) for each model year for the two types of programs.

- The portion of workers who are employed in the Bzone participate in a strong travel options program.
- The portion of households in the Bzone that participate in travel options programs tailored to the household.

Within the U.S., it is more often the case that workers participate in the travel options programs which then mostly affects the commute trip. Delivering the household side of the program occurs less frequently but still reduces overall vehicle trip making when available.

FCOG provided estimates for employee travel demand management program participation in the model region by Census geography. This was crosswalked to Bzones and calculated as a weighted average using total employment as the weight.

TABLE 28: TRAVEL DEMAND MANAGEMENT SUMMARY

	2022		2046	
MAREA	IMPPROP	ECOPROP	IMPPROP	ECOPROP
FCOG	0.0%	1.3%	0.0%	1.3%
KCOG	0.0%	0.6%	0.0%	0.6%
KCAG	0.0%	1.9%	0.0%	1.9%
MCAG	0.0%	0.1%	0.0%	0.1%
MCTC	0.0%	0.3%	0.0%	0.3%
SJCOG	0.0%	0.7%	0.0%	0.7%
StanCOG	0.0%	0.5%	0.0%	0.5%
TCAG	0.0%	1.2%	0.0%	1.2%

Data valid as of 9.29.25

bzone_unprotected_area.csv

Category: Land use

This file contains data on developable areas within a Bzone. Data from the 2022 Census Urban Areas dataset was used to determine urban, town, and rural areas in the model region. Urban areas with a population of less than 50,000 were marked as towns. Areas with no urban or town designations were considered rural. Additionally, areas designated as water bodies and protected land were removed. The total area for each area type for each Azone was spatially calculated using GIS tools. No changes were assumed for 2046.

TABLE 29: UNPROTECTED (DEVELOPABLE) AREA IN ACRES BY TYPE

MAREA	YEAR	URBANAREA	TOWNAREA	RURALAREA
FCOG	2022	99,503	25,822	2,169,039
FCOG	2046	99,503	25,822	2,169,039
KCOG	2022	82,630	35,385	3,643,891
KCOG	2046	82,630	35,385	3,643,891
KCAG	2022	11,435	13,586	842,416
KCAG	2046	11,435	13,586	842,416
MCAG	2022	27,173	10,484	1,109,462
MCAG	2046	27,173	10,484	1,109,462
MCTC	2022	14,135	3,116	849,571
MCTC	2046	14,135	3,116	849,571
SJCOG	2022	98,928	3,877	776,864
SJCOG	2046	98,928	3,877	776,864
StanCOG	2022	53,986	9,912	846,433
StanCOG	2046	53,986	9,912	846,433
TCAG	2022	45,212	9,994	1,484,648
TCAG	2046	45,212	9,994	1,484,648

Data valid as of 11.21.25

bzone_urban-mixed-use_prop.csv

Category: Land use

This input file helps assign specific values for the share of urban households (this only applies for urban areas) in mixed use neighborhoods. If there is no value assigned (NA), the model estimates the value using a model. The model uses other inputs such as population density, employment density, jobs to household ratios and destination accessibility of the zone to the mean number of jobs within two miles and population within five miles. These data are all part of other input files. The input is either NA or a value between 0 and 1 for each Bzone in the model region for each model year. The input is used in a module within VisionEval to assign households to mixed-use neighborhoods which then affects walking, biking, and overall vehicle trip use as more trips can be completed by active modes and using short trip lengths. The input file is also helpful to account for changes in the future which may not be well captured by the density and accessibility measures in the model that assigns whether the household is in a mixed-use neighborhood. When specifying inputs other than NA, local input is valuable to identify which Bzones and to what degree the households are in mixed use neighborhoods. SJV-VE currently assigns a value of NA for all Bzones in the model. The outputs from the model will show create an estimate of households within mixed use neighborhoods based on population and employment density outputs.

bzone_urban-town_du_proportions.csv

Category: Land use

This file contains information on the proportion of dwelling units within urban and non-urban portions of each Bzone. This data is divided into the proportion of single family, multi family, and group quarters dwelling units in urban areas versus town areas. The 2010 Census and Urban Rural Classifications were used to determine the proportion of households in a Bzone that are located in urban or town areas. Urbanized areas with a population of 50,000 or more were considered urban, while urbanized areas with a population less than 50,000 were considered towns.

TABLE 30: URBAN TOWN DWELLING UNIT PROPORTIONS

				2022				
	FCOG	**KCAG**	**KCOG**	**MCAG**	**MCTC**	**SJCOG**	**StanCOG**	**TCAG**
PropUrbanSFDU	68%	48%	62%	52%	42%	85%	77%	57%
PropUrbanMFDU	68%	48%	62%	52%	42%	85%	77%	57%
PropUrbanGQDU	68%	48%	62%	52%	42%	85%	77%	57%
PropTownSFDU	32%	50%	37%	46%	58%	14%	23%	42%
PropTownMFDU	32%	50%	37%	46%	58%	14%	23%	42%
PropTownGQDU	32%	50%	37%	46%	58%	14%	23%	42%
				2046				
	FCOG	**KCAG**	**KCOG**	**MCAG**	**MCTC**	**SJCOG**	**StanCOG**	**TCAG**
PropUrbanSFDU	68%	48%	62%	52%	42%	85%	77%	57%
PropUrbanMFDU	68%	48%	62%	52%	42%	85%	77%	57%
PropUrbanGQDU	68%	48%	62%	52%	42%	85%	77%	57%
PropTownSFDU	32%	50%	37%	46%	58%	14%	23%	42%
PropTownMFDU	32%	50%	37%	46%	58%	14%	23%	42%
PropTownGQDU	32%	50%	37%	46%	58%	14%	23%	42%

Valid as of 9.25.25

deflators.csv

Category: Setup

This file defines annual deflator values, such as the Consumer Price Index, and should be stored in the “defs” folder. The file does not require any changes. The version of this file includes the following points for comparing to other versions.

TABLE 31: DEFLATORS

YEAR	VALUE
1990	130.66

2022	299.87
2046	504.53
2050	550.41

geo.csv

Category: Setup

This file describes all geographies within the VisionEval model region. This file was modified to contain all of the geographic information within the San Joaquin Valley model region.

marea_base_year_dvmt.csv

Category: Setup

This file contains DVMT in urbanized portions of the Marea split by light-duty vehicles (passenger vehicles) and heavy trucks during the base year. The file allows the user to adjust DVMT growth factors in the base year by Marea. Light-duty and heavy truck DVMT were obtained from the travel demand model network of each county. If the network did not include truck volume, HPMS data was used to calculate percentage of truck volume and applied to the loaded network total volume.

TABLE 32: MAREA BASE YEAR DVMT SUMMARY

MAREA	UZANAME	URBANLDVDVMT	URBANHVYTRKDVMT
FCOG	NA	11,021,626	3,356,640
KCOG	NA	9,608,578	596,912
KCAG	NA	797,901	63,916
MCAG	NA	2,131,112	129,731
MCTC	NA	982,762	53,115
SJCOG	NA	46,473	4,708
StanCOG	NA	6,451,807	165,114
TCAG	NA	2,951,164	340,702

Data valid as of 11.3.25

marea_congestion_charges.csv

Category: Pricing

This optional file accounts for policies on congestion charges and tolling. The file assigns a per mile fee for any miles of travel which may occur at different congestion thresholds on freeways/throughways and arterials. Specifically, the congestion levels are None, Moderate, Heavy, Severe, and Extreme. The file is used to estimate what the future conditions are expected to be and whether the region anticipates implementing any tolling or congestion charges on I-5 or arterials in the region.

No congestion charges were assigned to the San Joaquin Valley Mareas.

marea_dvmt_split_by_road_class.csv

Category: Systems Operations/ITS

This file inputs the DVMT split by road class and vehicle type for all model years (e.g. light duty vehicle DVMT on freeways, arterial roads, or other roads in urbanized areas of the Marea). This input was calculated based on the volumes of the travel demand model networks for each county. For networks without truck volume, HPMS was used to calculate the percentage of truck volume and applied to the total volume in the network. Bus DVMT was collected from NTD. Commuter mode was assumed to move only on freeway, while standard bus, only on arterials.

TABLE 33: MAREA DVMT SPLIT BY ROAD CLASS

	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
LdvFwyDvmtProp	0.30	0.00	0.24	0.39	0.57	0.63	0.33	0.32
LdvArtDvmtProp	0.33	0.95	0.37	0.19	0.21	0.26	0.20	0.35
LdvOthDvmtProp	0.37	0.05	0.39	0.42	0.22	0.11	0.47	0.33
HvyTrkFwyDvmtProp	0.44	0.00	0.24	0.39	0.57	0.64	0.33	0.48
HvyTrkArtDvmtProp	0.26	1.00	0.37	0.19	0.21	0.27	0.20	0.26
HvyTrkOthDvmtProp	0.30	0.00	0.39	0.42	0.22	0.09	0.47	0.26
BusFwyDvmtProp	0.00	0.00	0.00	0.00	0.58	0.11	0.00	0.00
BusArtDvmtProp	1.00	1.00	1.00	1.00	0.42	0.89	1.00	1.00
BusOthDvmtProp	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Data valid as of 10.2.25

marea_lane_miles.csv

Category: Systems Operations/ITS

This input file contains information on the quantity of lane miles (as opposed to centerline miles) for freeway/throughways and arterial lane-miles within each Marea. The input file was produced by aggregating the lane miles in the travel model networks by road type. Base year miles were calculated using the base networks and future miles from the future networks. SJCOG did not provide a future network and therefore no changes are assumed for 2046. For KCOG, HPMS data was used to calculate base year lane miles, and for 2046 estimates, the percentage increase from the travel model networks was applied as a growth factor.

TABLE 34: MAREA ROADWAY LANE MILES

MAREA	YEAR	FWYLANEMI	ARTLANEMI
FCOG	2022	659	2,288
FCOG	2046	660	2,592
KCOG	2022	399	6,305
KCOG	2046	399	6,647
KCAG	2022	177	464
KCAG	2046	177	489
MCAG	2022	328	528
MCAG	2046	351	561
MCTC	2022	152	801
MCTC	2046	253	937
SJCOG	2022	668	640
SJCOG	2046	668	640
StanCOG	2022	263	426
StanCOG	2046	287	488
TCAG	2022	381	934
TCAG	2046	443	1,060

Data valid as of 11.21.25

marea_operations_deployment.csv

Category: Systems Operations/ITS

This optional input file is used to reflect changes in the vehicle operations on freeway and arterial facilities resulting from enhancements such as ramp meters (on-ramp signals), signal coordination (arterial green-wave coordination), access management (driveway consolidation, remove left-turns), incident management deployment (cameras and systems to remove stalled vehicles or crashes as quickly as possible to reduce non-recurrent delay), and other undefined system operation improvements. Data for this input was developed by FCOG using Caltrans deployment data.

TABLE 35: SYSTEM OPERATIONS DEPLOYMENT

	2022							
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
RampMeterDeployProp	36%	3%	0%	0%	0%	26%	28%	0%
IncidentMgtDeployProp	77%	52%	33%	25%	76%	50%	46%	81%
SignalCoordDeployProp	0%	0%	0%	0%	0%	0%	0%	0%
AccessMgtDeployProp	0%	0%	0%	0%	0%	0%	0%	0%
OtherFwyOpsDeployProp	0%	0%	0%	0%	0%	0%	0%	0%
OtherArtOpsDeployProp	0%	0%	0%	0%	0%	0%	0%	0%

	2046							
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
RampMeterDeployProp	56%	21%	0%	3%	29%	67%	67%	18%
IncidentMgtDeployProp	81%	56%	46%	37%	78%	62%	56%	86%
SignalCoordDeployProp	0%	0%	0%	0%	0%	0%	0%	0%
AccessMgtDeployProp	0%	0%	0%	0%	0%	0%	0%	0%
OtherFwyOpsDeployProp	0%	0%	0%	0%	0%	0%	0%	0%
OtherArtOpsDeployProp	0%	0%	0%	0%	0%	0%	0%	0%

Data valid as of 10.29.25

marea_safety_factors

Category: Systems Operations/ITS

Transportation crash rates are defined by the number of injuries or fatalities per 100 million miles traveled for autos, and injuries or fatalities per 1 million miles traveled for all other modes. Crash data was provided by FCOG and sourced from the Statewide Integrated Traffic Records System (SWITRS).

TABLE 36: SAFETY FACTORS SUMMARY

	2022							
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	StanCOG	TCAG
AutoFatal	1.38	1.49	2.37	1.48	1.63	1.36	1.01	1.81
AutoInjur	35.12	30.27	29.67	50.31	33.03	48.00	51.18	40.82
BikeFatal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BikeInjur	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
WalkFatal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WalkInjur	0.00	0.01	0.00	0.01	0.01	0.00	0.02	0.01
BusFatal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BusInjur	0.12	0.02	0.03	0.03	0.02	0.03	0.07	0.05
RailFatal	0.00	1.86	0.00	1.86	0.00	0.94	0.00	0.00
RailInjur	0.00	3.71	0.00	0.00	0.00	0.00	7.25	0.00
	2046							
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	StanCOG	TCAG
AutoFatal	1.38	1.49	2.37	1.48	1.63	1.36	1.01	1.81
AutoInjur	35.12	30.27	29.67	50.31	33.03	48.00	51.18	40.82
BikeFatal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BikeInjur	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
WalkFatal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WalkInjur	0.00	0.01	0.00	0.01	0.01	0.00	0.02	0.01

BusFatal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BusInjur	0.12	0.02	0.03	0.03	0.02	0.03	0.07	0.05
RailFatal	0.00	1.86	0.00	1.86	0.00	0.94	0.00	0.00
RailInjur	0.00	3.71	0.00	0.00	0.00	0.00	7.25	0.00

Data valid as of 9.16.25

marea_speed_smooth_ecodrive.csv

Category: Systems Operations/ITS

This input file supplies information on deployment of speed smoothing and ecodriving by road class and vehicle type. Although these behavioral programs have recently decreased in visibility nationwide, there are still modest ongoing efforts to influence behavior to encourage smooth acceleration and braking for light duty and heavy-duty vehicles. In addition, speed smoothing actions such as traffic management through variable message signage (VMS) including variable speed limits and signal coordination are intended to be captured by this input. The input is a fractional share of vehicles by roadway type (freeway/throughway and arterial) participating or benefiting from each program. Local input should be given as to whether these values reflect historical values accurately and represent future actions. This value is assumed to be 0 for the San Joaquin Valley model.

TABLE 37: SPEED SMOOTHING POLICY UPTAKE

YEAR	FWYSMOOTH	ARTSMOOTH	LDVECODRIVE	HVYTRKECODRIVE
2022	0	0	0	0
2046	0	0	0	0

Data valid as of 9.29.25

marea_transit_ave_fuel_carbon_inten.csv

Category: Vehicles & fuels

This file is used to adjust the average fuel carbon intensity in grams of CO2e per megajoule by mode within an Marea. Data for this input was sourced from the carbon intensities listed under Low Carbon Fuel Standard (LCFS) data.[28] Future year reductions were informed by the LCFS goal for 2045, which aims to reduce transit vehicle emissions by 90%.[29]

TABLE 38: FUEL CARBON INTENSITY

YEAR	TRANSITVANFUELCI	TRANSITBUSFUELCI	TRANSITRAILFUELCI

[28] https://ww2.arb.ca.gov/resources/documents/lcfs-data-dashboard
[29] https://ww2.arb.ca.gov/news/carb-updates-low-carbon-fuel-standard-increase-access-cleaner-fuels-and-zero-emission

2022	77.9	77.9	77.9
2046	9.5	9.5	9.5

Data valid as of 9.18.25

marea_transit_biofuel_mix.csv

Category: Vehicles & fuels

This input is used to modify the amount of biofuel used by transit in a given year. FCOG staff provided this input based on LCFS fuel mix data. No change was assumed between model years, and the biofuel mix was applied across the model region.

TABLE 39: TRANSIT BIOFUEL MIXTURE

VARIABLE	2022	2046
TransitEthanolPropGasoline	10.0%	10.0%
TransitBiodieselPropDiesel	7.5%	7.5%
TransitRngPropCng	96.6%	96.6%

Data Valid as of 9.30.25

marea_transit_fuel.csv

Category: Vehicles & fuels

This input allows the user to modify transit fuels proportions, such as bus proportion gasoline or CNG. This data was provided by FCOG and is sourced from California Air Resources Board (CARB) EMFAC data.[30] Fuel shares were applied specific to each MPO subregion.

TABLE 40: TRANSIT FUEL SHARES

	2022							
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
BusPropDiesel	17.3%	20.0%	16.7%	52.4%	20.8%	45.3%	50.5%	23.7%
BusPropGasoline	44.6%	52.0%	55.3%	47.5%	70.9%	46.2%	30.6%	34.0%
BusPropCng	38.1%	28.0%	27.9%	0.1%	8.2%	8.5%	18.9%	42.3%
VanPropDiesel	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
VanPropGasoline	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
VanPropCng	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
RailPropDiesel	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
RailPropGasoline	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	2046							

30 https://ww2.arb.ca.gov/our-work/programs/msei/on-road-emfac

	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
BusPropDiesel	87.0%	81.9%	62.0%	74.7%	82.2%	66.5%	89.5%	89.3%
BusPropGasoline	9.4%	17.4%	32.5%	24.7%	13.8%	26.6%	7.7%	8.8%
BusPropCng	3.6%	0.6%	5.4%	0.6%	4.0%	6.9%	2.8%	1.8%
VanPropDiesel	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
VanPropGasoline	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
VanPropCng	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
RailPropDiesel	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
RailPropGasoline	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Data valid as of 9.17.25

marea_transit_powertrain_prop.csv

Category: Vehicles & fuels

This input allows users to modify the proportion of powertrain types used by transit, including vans, buses, and rail. This data was provided by FCOG and is sourced from CARB EMFAC data.

TABLE 41: TRANSIT POWERTRAIN SHARES

				2022				
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
BusPropIcev	98.1%	98.6%	100.0%	100.0%	100.0%	96.8%	97.3%	91.7%
BusPropHev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
BusPropBev	1.9%	1.4%	0.0%	0.0%	0.0%	3.2%	2.7%	8.3%
VanPropIcev	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
VanPropHev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
VanPropBev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
RailPropIcev	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
RailPropHev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
RailPropEv	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
				2046				
	FCOG	KCOG	KCAG	MCAG	MCTC	SJCOG	STANCOG	TCAG
BusPropIcev	27.5%	30.4%	38.6%	34.4%	63.7%	34.9%	26.0%	25.1%
BusPropHev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
BusPropBev	72.5%	69.6%	61.4%	65.6%	36.3%	65.1%	74.0%	74.9%
VanPropIcev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
VanPropHev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
VanPropBev	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
RailPropIcev	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

RailPropHev	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
RailPropEv	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Data valid as of 9.29.25

marea_transit_service.csv

Category: Transportation options

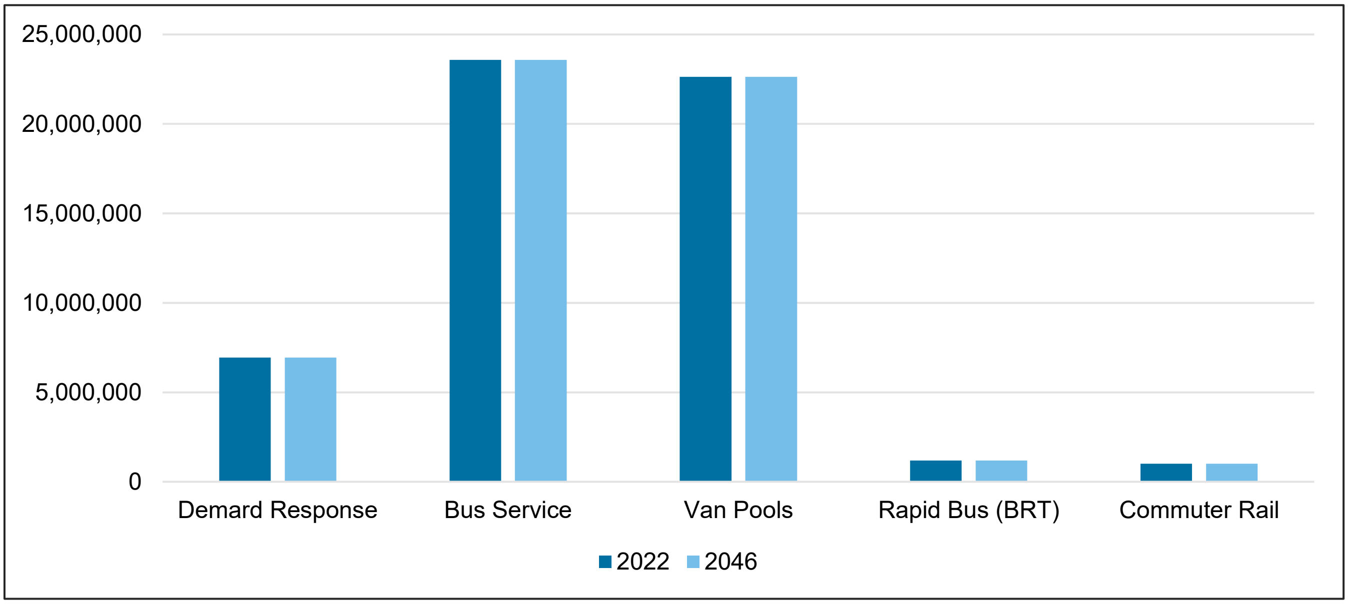
This file contains the annual revenue-miles for different transportation modes in the Marea, including demand response (DRRevMi), local bus (MBRevMi), van-pool (VPRevMi), rapid bus (RBRevMi), monorail (MGRevMi), streetcar (SRRevMi), heavy and light rail (HRRevMi), and commuter rail (CRRevMi). Revenue miles were calculated from the National Transit Database for 2024, accounting for all service providers within each respective MPO region. No changes were assumed for 2046. The chart below summarizes revenue miles by the prevalent modes.

TABLE 42: TRANSIT REVENUE MILES

				2022				
	FCOG	**KCOG**	**KCAG**	**MCAG**	**MCTC**	**SJCOG**	**STANCOG**	**TCAG**
DRRevMi	1,818,715	1,863,839	124,116	508,526	170,626	884,893	1,106,093	469,210
MBRevMi	5,955,700	4,362,787	715,824	2,092,403	253,314	2,991,097	3,855,463	3,353,672
VPRevMi	0	0	802,822	0	0	9,695,758	2,933,355	9,200,278
RBRevMi	0	0	0	0	287,615	310,133	346,908	249,894
CRRevMi	0	0	0	0	0	1,014,541	0	0
SRRevMi	0	0	0	0	0	0	0	0
HRRevMi	0	0	0	0	0	0	0	0
MGRevMi	0	0	0	0	0	0	0	0
				2046				
	FCOG	**KCOG**	**KCAG**	**MCAG**	**MCTC**	**SJCOG**	**STANCOG**	**TCAG**
DRRevMi	1,818,715	1,863,839	124,116	508,526	170,626	884,893	1,106,093	469,210
MBRevMi	5,955,700	4,362,787	715,824	2,092,403	253,314	2,991,097	3,855,463	3,353,672
VPRevMi	0	0	802,822	0	0	9,695,758	2,933,355	9,200,278
RBRevMi	0	0	0	0	287,615	310,133	346,908	249,894
CRRevMi	0	0	0	0	0	1,014,541	0	0
SRRevMi	0	0	0	0	0	0	0	0
HRRevMi	0	0	0	0	0	0	0	0
MGRevMi	0	0	0	0	0	0	0	0

Data valid as of 11.25.25

FIGURE 14: ANNUAL TRANSIT REVENUE MILES (MODEL REGION)



model_parameters.json

Category: Setup

Contains global parameters for the model configuration for multiple modules. The variables listed in the file can be modified to run different scenarios depending on user preference. This file was not modified for use in this model.

other_ops_effectiveness.csv

Category: Systems Operations/ITS

This input modifies delay effects of operations in different road class types, such as recurring and non-recurring arterial and freeway delays. This input uses default VisionEval values.

TABLE 43: OTHER OPS PROGRAMS

LEVEL	ART_RCR	ART_NONRCR	FWY_RCR	FWY_NONRCR
None	0	0	0	0
Mod	0	0	0	0
Hvy	0	0	0	0
Sev	0	0	0	0
Ext	0	0	0	0

region_ave_fuel_carbon_intensity.csv

Category: Vehicles & fuels

This input modifies the average carbon intensity for different vehicle types for the model region. This accounts for upstream GHG emissions associated with the combustion of fossil fuel. This input mirrors low carbon fuel standard (LCFS) policies to reduce 2020 emissions values by 90% by 2045.[31]

TABLE 44: FUEL CARBON INTENSITY

VARIABLE	2022	2046
HhFuelCI	89.5	9.2
CarSvcFuelCI	89.5	9.2
ComSvcFuelCI	89.5	9.2
HvyTrkFuelCI	90.4	9.3
TransitVanFuelCI	89.5	9.2
TransitBusFuelCI	90.4	9.3
TransitRailFuelCI	89.5	9.2

Data valid as of 8.25.25

region_base_year_dvmt.csv

Category: Setup

This input is used to adjust regional heavy truck DVMT for the base year. This is calculated from the MPO travel model networks. For networks with no assigned truck volume, the percentage of truck volume was estimated from HPMS and applied to the total network volume. The input asserts that the growth in heavy truck VMT is proportional to the growth in real income and growth in changes in commercial truck VMT is proportional to the growth in population.

TABLE 45. HEAVY TRUCK AND COMMERCIAL TRUCK VOLUME GROWTH

STATEABBRLOOKUP	HVYTRKDVMT GROWTHBASIS	HVYTRK DVMT	COMSVCDVMT GROWTHBASIS
NA	Income	31,708,294	Population

Data valid as of 11.3.25

[31] https://ww2.arb.ca.gov/sites/default/files/2020-09/basics-notes.pdf

region_carsvc_powertrain_prop.csv

Category: Vehicles & fuels

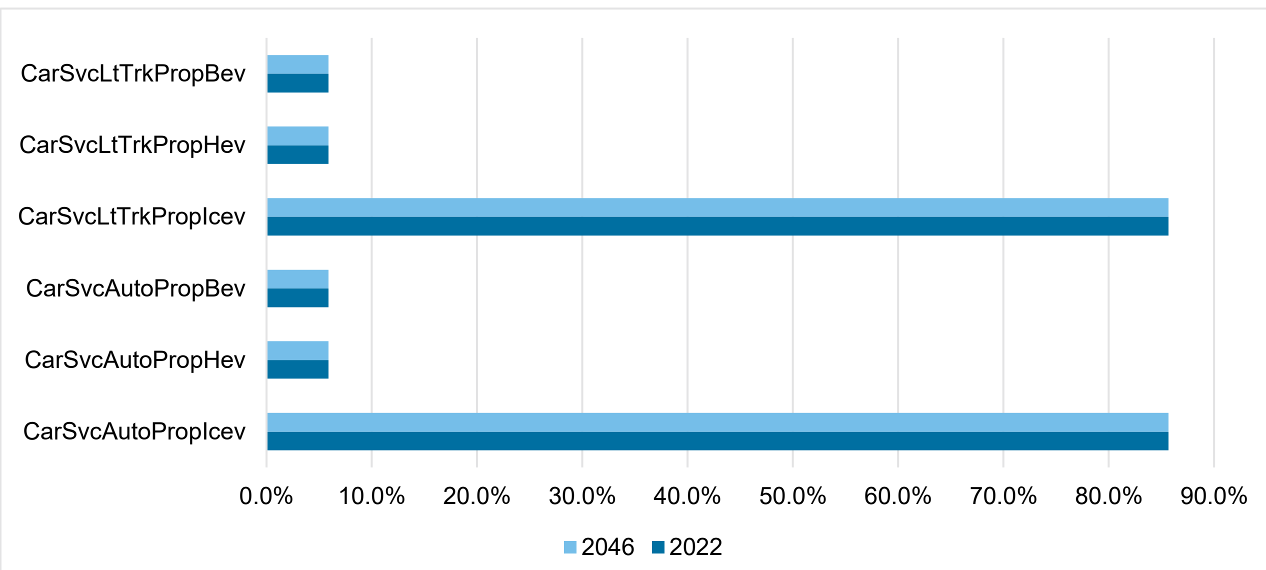
This input is used to adjust the powertrain proportion of car services, specifically adjustments to the proportion of fleet vehicles that are combustion engine, battery electric, or hybrid electric. This input is built using California vehicle registration data by fuel and powertrain type for 2022 and is filtered to only vehicles that are 7 years old or newer. No changes were assumed for 2046.

TABLE 46: CAR SERVICE POWERTRAIN SHARES

VARIABLE	2022	2046
CarSvcAutoPropIcev	85.7%	85.7%
CarSvcAutoPropHev	5.9%	5.9%
CarSvcAutoPropBev	5.9%	5.9%
CarSvcLtTrkPropIcev	85.7%	85.7%
CarSvcLtTrkPropHev	5.9%	5.9%
CarSvcLtTrkPropBev	5.9%	5.9%

Data valid as of 8.25.25

FIGURE 15: CAR SERVICE VEHICLE POWERTRAINS



Data valid as of 8.25.25

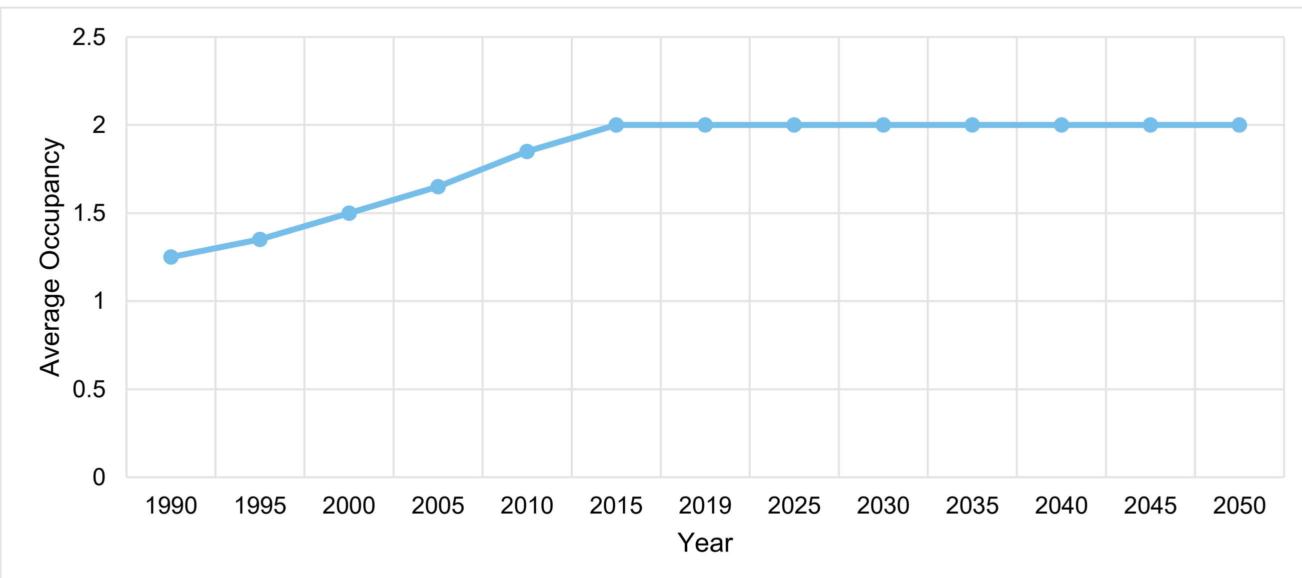
region_carsvc_shd_occup.csv

Category: Transportation options

This input accounts for the changes and incentives through pricing and social norms that change the average occupancy for car service options. Estimates are provided for this with local input informing future conditions. Changing the occupancy of the car service will reduce the net number of road miles consumed by vehicles, reduce the greenhouse gas emissions and fuel consumed, and reduce the travel cost of a household.

The user input guiding the occupancy of shared car service can be used to evaluate various policy objectives and effects on the transportation network. Because travel is estimated at the household level, it is hard to approximate the VMT savings on the individual household; however, the emissions and total roadway daily vehicle miles traveled (DVMT) will reflect changes in VMT that would be saved due to the increased pooled rides.

FIGURE 16: SHARED CAR SERVICE VEHICLE OCCUPANCY



Data valid as of 9.29.25

region_co2e_costs.csv

Category: Pricing

This input accounts for the environmental and social costs of CO_2 emissions per metric ton, with the USD value based on the model year. These costs reflect 2016 EPA projections for the social cost of carbon.[32]

TABLE 47: SOCIAL COSTS OF CARBON

YEAR	CO2ECOST.2007
2022	$46 per metric ton
2046	$64 per metric ton

Data valid as of 9.24.25

region_comsvc_lttrk_prop.csv

Category: Vehicles & fuels

This input defines the proportion of commercial vehicles that are light trucks within the model region. This input uses VisionEval default values.

TABLE 48: COMMERCIAL VEHICLE LIGHT TRUCK SHARE

YEAR	COMSVCLTTRKPROP
2022	51%
2046	51%

Data valid as of 8.25.25

region_comsvc_powertrain_prop.csv

Category: Vehicles & fuels

This input is used to adjust the powertrain proportion of commercial vehicles, specifically adjustments to the proportion of fleet vehicles that are combustion engine, battery electric, or hybrid electric. This input follows policies in CARB Advanced Clean Trucks and Advanced Clean Fleets regulations, which sets goals of 100% EV trucks by 2046.[33]

TABLE 49: COMMERCIAL SERVICE POWERTRAINS

YEAR	2022	2046
ComSvcAutoPropIcev	99%	0%
ComSvcAutoPropHev	1%	0%
ComSvcAutoPropBev	0%	100%

[32] https://ww2.arb.ca.gov/sites/default/files/2020-04/2018_10_24_auffhammer_uc_berkeley_social_cost_of_carbon_ac_2.pdf
[33] https://ww2.arb.ca.gov/our-work/programs/truckstop-resources/zev-truckstop/zev-101/californias-plan-zero-emission-vehicles

ComSvcLtTrkPropIcev	100%	0%
ComSvcLtTrkPropHev	0%	0%
ComSvcLtTrkPropBev	0%	100%

Data valid as of 8.25.25

region_comsvc_veh_mean_age

Category: Vehicles & fuels

This input contains the average age of commercial service vehicles. This input uses VisionEval default values.

TABLE 50: COMMERCIAL SERVICE AVERAGE VEHICLE AGE

YEAR	AVECOMSVCVEHICLEAGE
2022	3 years
2046	3 years

Data valid as of 8.25.25

region_hvytrk_powertrain_prop.csv

Category: Vehicles & fuels

This input specifies the powertrain proportions of heavy-duty trucks, specifically adjustments to the proportion of fleet vehicles that are combustion engine, battery electric, or hybrid electric. This input was developed using California vehicle registration data and matches the heavy truck powertrain goals set in CARB's Advanced Clean Trucks and Advanced Clean Fleets goals.

TABLE 51: HEAVY TRUCK VEHICLE POWERTRAINS

YEAR	HVYTRKPROPICEV	HVYTRKPROPHEV	HVYTRKPROPBEV
2022	99.6%	0%	0.4%
2046	0%	0%	100%

Data valid as of 11.12.25

region_prop_externalities_paid.csv

Category: Pricing

This input contains the proportion of external costs for the region, such as climate change and social costs. San Joaquin Valley estimates were produced using CARB's 2022 market cost of carbon estimates and California EPA estimates of the social cost of carbon.[34, 35] No changes were assumed for future years.

TABLE 52: SOCIAL AND ENVIRONMENTAL COSTS ADDED TO VMT

YEAR	PROPCLIMATECOSTPAID	PROPOTHEREXTCOSTPAID
2022	12.6%	0%
2046	12.6%	0%

Data valid as of 9.29.25

region_road_cost.csv

Category: Systems Operations/ITS

This input contains infrastructure costs used to estimate the light duty vehicles DVMT fee to fully recover road costs such as per lane mile arterial and freeway costs. This input uses VisionEval default values.

TABLE 53: ROAD COST SUMMARY

YEAR	2022	2046
RoadBaseModCost.2005	$0.004	$0.004
RoadPresOpMaintCost.2005	$0.010	$0.010
RoadOtherCost.2005	$0.015	$0.015
FwyLnMiCost.2005	$4,900	$4,900
ArtLnMiCost.2005	$1,800	$1,800
HvyTrkPCE	2	2

Data valid as of 9.29.25

region_telework.csv

Category: Transportation options

Overview

Teleworking has become ubiquitous for a sizeable share of the US workforce as a consequence and response to the COVID-19 pandemic. Before the pandemic, teleworking was largely considered a worthwhile travel demand management (TDM) action intended to reduce travel miles associated with commutes to a fixed place of work.

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34 https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/program-data/cap-and-trade-program-data-dashboard

35 https://calepa.ca.gov/wp-content/uploads/2025/01/affordability-calculations-sourced.xlsx

Accounting for teleworking in travel demand models, including the strategic demand model VisionEval, is challenging given the relationships between individual employee – employer dynamics, the household composition (represented as "life cycle" in National Household Travel Data), the occupation, distance and travel options to work, etc.

RSG has been studying teleworking behavior as part of household travel surveys conducted on behalf of regions and states often as part of a travel demand model update. RSG expanded the survey program in May 2020 to create a longitudinal panel survey to monitor travel behavior changes during the significant upheaval associated with the COVID-19 pandemic. The following notable changes in travel behavior were observed in the data of survey responses[36]:

- Online grocery orders and delivery will likely continue to supplement in-store shopping, particularly among high-income and zero-vehicle households.
- Similarly, telehealth will likely continue to supplement in-person appointments, especially among adults in households with children.
- Income continues to significantly influence telework access, which in turn impacts telework access among Black and Hispanic residents.

Definition of Teleworking

Defining "teleworking" is essential to create a model and a consistent set of data by which to estimate that model on. The term "teleworking" is quickly becoming the accepted term that refers to all work types which are undertaken that exclude an actual journey-to-work trip. Thus, working at home after a day which included a commute is not an example of teleworking; nor is any day which includes a commute to a workplace, or a unit of work undertaken on a day not normally including a commute trip.

Rather, the broadly inclusive term teleworking includes all work undertaken remotely, whether at the home or a location other than the workplace, including from a coffee shop, or working at a location that serves as an alternative to the dominant workplace. Thus, it specifically includes both those who sometimes commute to a workplace, *and* those who only work at home.

While there is a wide variation in the definition of what constitutes "working-from-home", there was general agreement between some of the three most consequential research efforts on this topic. The resulting preferred metric is the portion of work days served by either commute or located at home expressed as a percentage of total employed days.

[36] The RSG COVID panel started in May 2020. It continued through Sept 2021 with nine waves. Additional surveys were later administered and added to the data sample. Each wave had over 3000 participants and weighted to be statistically representative of the national population. See this survey summary for additional information: https://rsginc.com/wp-content/uploads/2022/01/How-COVID-19-Necessities-Have-and-Havent-Changed-the-Way-People-Travel.pdf

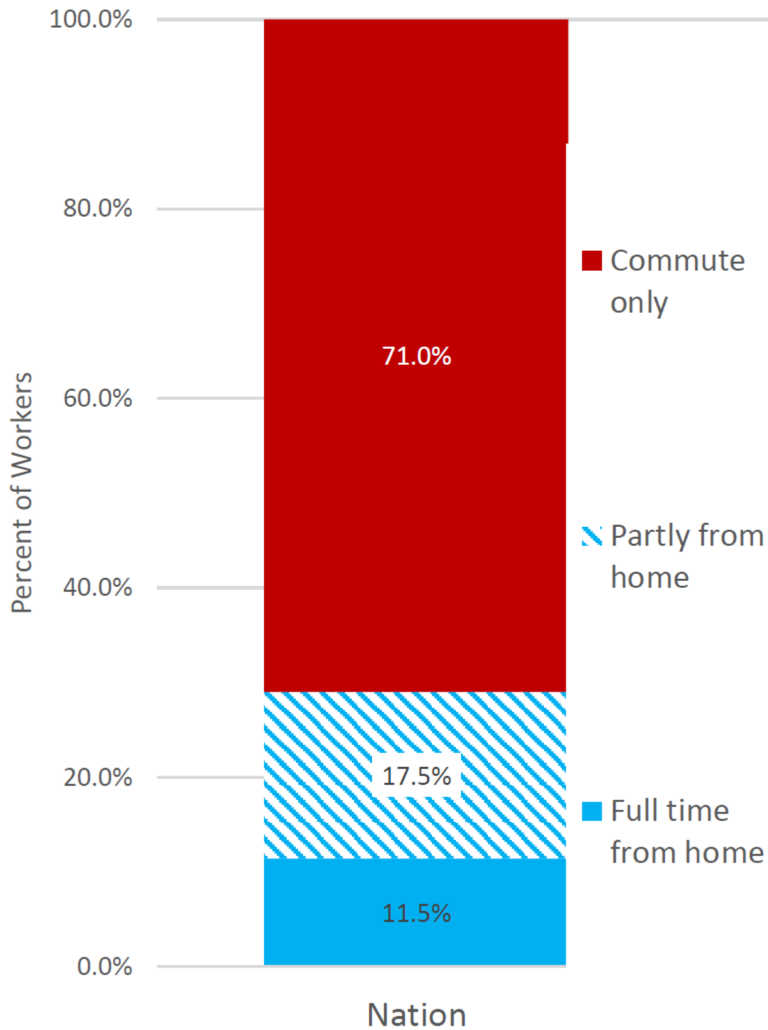
The literature and the data support the notion that there are two primary types of workers who may work from home, and it is important to distinguish which types are being referred to in the various data.

- Type 1: home-based business workers. This group is a subcategory of the NHTS category called “WFH Only,” describing those that have their employment address matching their home address. It includes a broad array of workers.
- Type 2: telecommuters. This is the second subcategory, which describes workers that are using technology to replace a physical commute or travel to a place of work. Their home is not the same address as their place of employment, although they may do their work from their home. A subset of this group may also work in a third location, such as a library, coffee shop, or shared working environment (e.g., We Work).

The NHTS defines the WFH Only workers as those who “did work in the last week for pay or profit” and did not have a regular workplace outside the home. The WFH Only classification encompasses the Type 1 home-based workers and the full-time Type 2 teleworkers. This overlap is important to acknowledge that Type 2 includes full time as part of part-time, hybrid, telecommuters.

The 2017 NHTS commute characteristic is shown in Figure 17~~Figure 17~~. The important takeaway is that behaviors are complex and commute patterns can be mixed, with some days home based vs some days fixed workplace based.

FIGURE 17: PRE-COVID US COMMUTE CHARACTERISTICS IN THREE GROUPS

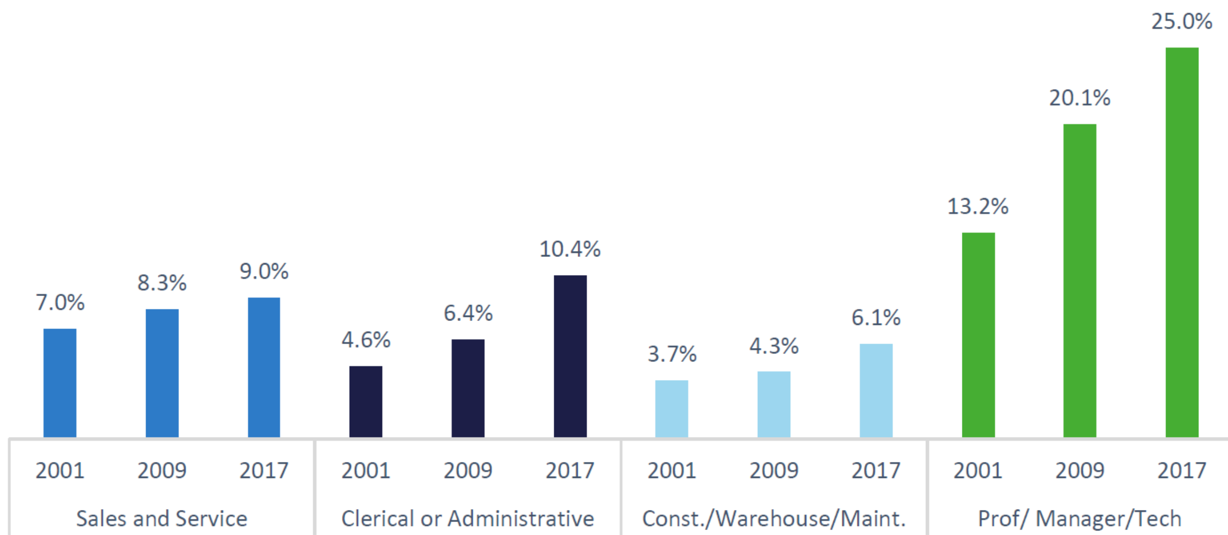


Source: 2017 NHTS

Worker Occupation

The NHTS provides additional data on the characteristics of the worker, including income, education, and critically – the worker occupation. Figure 18Figure 18 shows a longitudinal analysis of various NHTS datasets showing a relationship over time between occupational codes and the propensity to telework. These rates show the historical trend towards greater teleworking pre-pandemic.

FIGURE 18: TRENDS IN TELEWORKING, BY OCCUPATION PRE-PANDEMIC



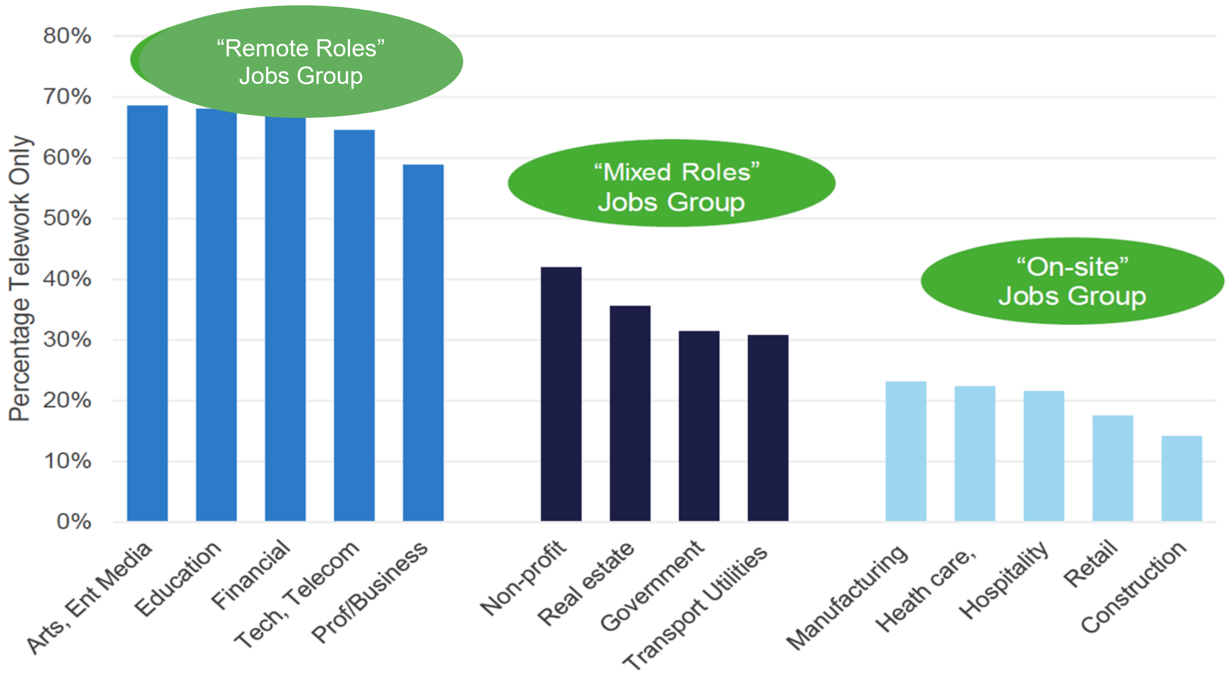
Source: RSG analysis of NHTS Data Series 2001 – 2017

RSG observed similar relationships within the RSG COVID panel survey data. Three clusters were created to align with the general degree of teleworking observed during the survey period. The three teleworking categories of "remote", "mixed", and "on-site" were derived to group occupations which had similar travel behaviors. The simplification of three teleworking categories was important to reduce the data burden and computation time for modeling the effects of teleworking on overall travel behavior in travel models, namely VisionEval.

The categories were defined based on the literature review done in Massachusetts, the COVID-19 Survey, and an extensive analysis of a longitudinal household travel survey in Ohio using an rMove dataset made available to relate workers' occupation to travel behavior. Occupational data had a stronger relationship with teleworking than workplace industry classification (i.e., NAICS), however, occupational data is less frequently sampled or available than industry data.

Figure 19~~Figure 19~~ shows the generalized teleworking rates for different occupations by teleworking category.

FIGURE 19: TELEWORKING CATEGORY DEFINITION – PEAK PANDEMIC RATES



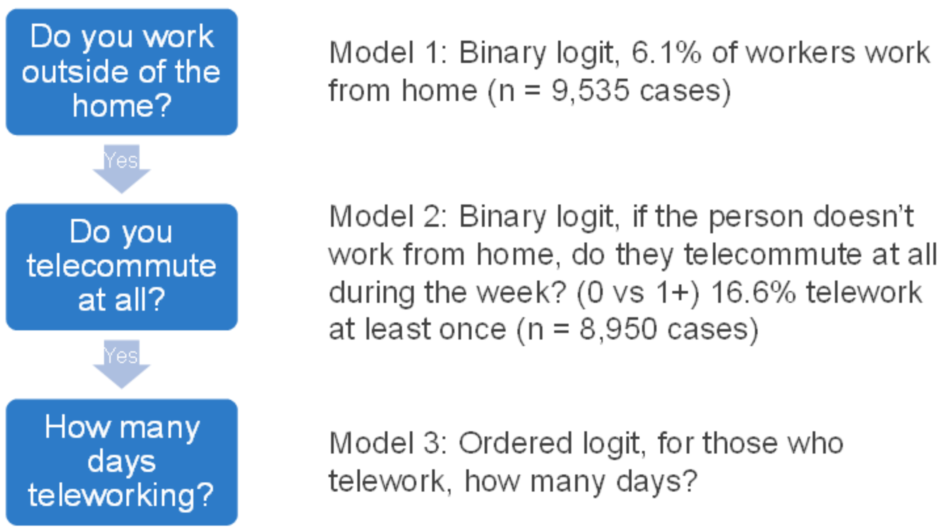
Source: RSG

RSG used detailed information on the worker occupation, area type (urban, town, rural), and commute distances from the SWIM statewide model. The occupation categories are informed from the Bureau of Labor Statistics (BLS) Standardized Occupational Codes (SOC) to classify the employed persons into the three categories associated with their propensity to telework.

Modeling Teleworking Travel Behavior

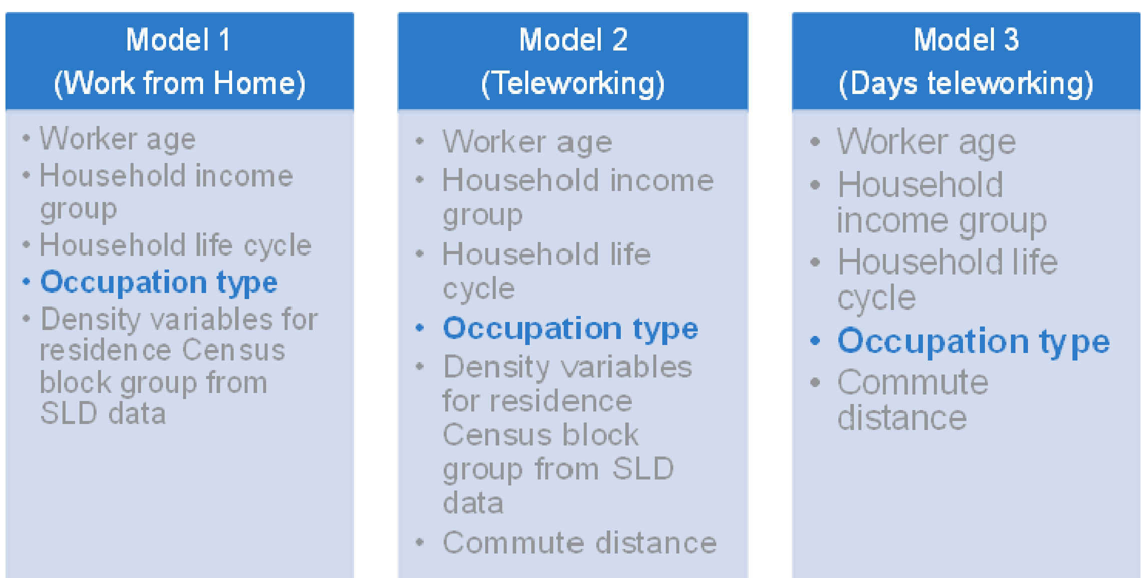
The data above informed a new Teleworking Module within the VisionEval framework. The teleworking module includes three core models as shown in Figure 20~~Figure 20~~.

FIGURE 20: TELEWORKING MODEL SEQUENCE



Each of the three models uses a similar set of explanatory variables as shown below. The Occupation Type is the new assertion that needs to be added to the VisionEval model through a new model input.

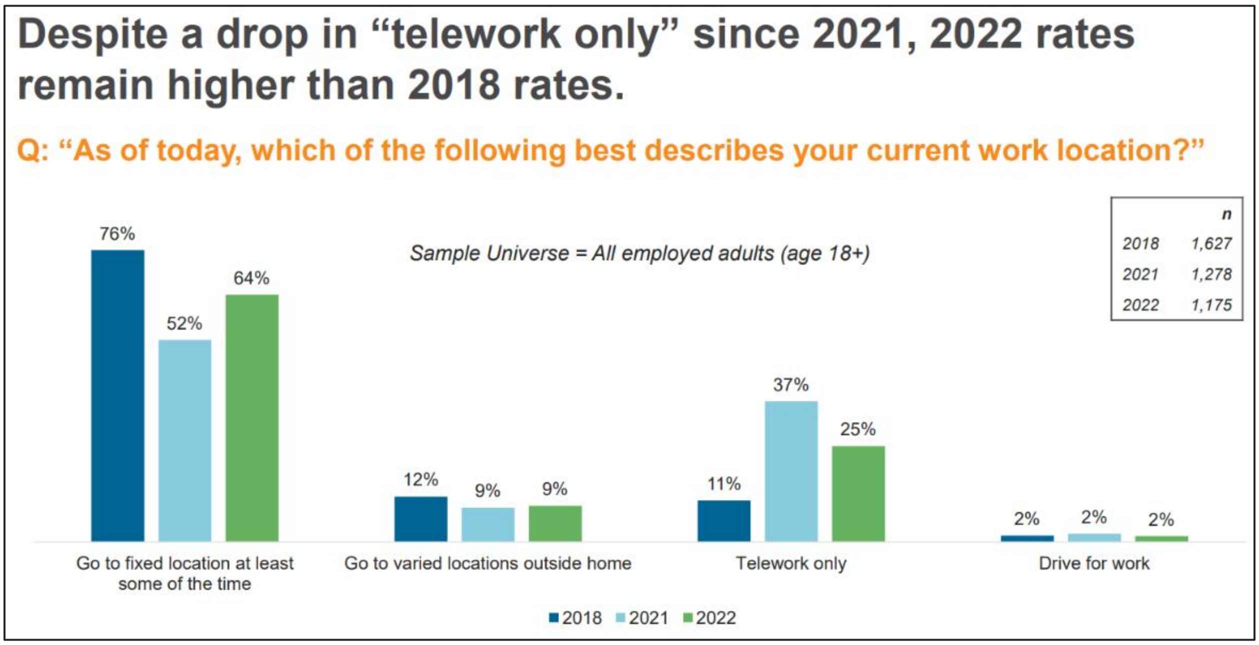
FIGURE 21: TELEWORKING MODEL COMPONENTS



These statistical models are included in the VisionEval Teleworking Module structure using an input file that estimates the percentage of workers within each of the three teleworking categories by the location type in the VisionEval model (urban, town, or rural).

The VisionEval model can be used to test changes in the level of teleworking across the different occupation teleworking categories. RSG's ongoing surveys of teleworking can inform the design of future scenarios to test within the Metro analysis. Although for reasons mentioned earlier, there are slight differences between different datasets, the 2018 pre-covid data shown in the RSG data charted below are generally consistent with the other surveys and datasets mentioned previously. The 2022 conditions for teleworking do show a reduction in teleworking relative to the levels earlier in the pandemic but they remain higher than higher than historical pre-covid norms.

FIGURE 22: TELEWORKING AS SHARE OF WORK LOCATION



Source: TRB '23 Rosenson, A. RSG

This input contains the teleworking rates for the model region by type and year, as shown in Table 54~~Table 54~~. The San Joaquin Valley values were developed using working from home rates in 2022 defined by Bureau of Labor Statistics data on working from home for each MPO. Rates were assumed to be unchanged in 2046.

TABLE 54: TELEWORKING INPUT

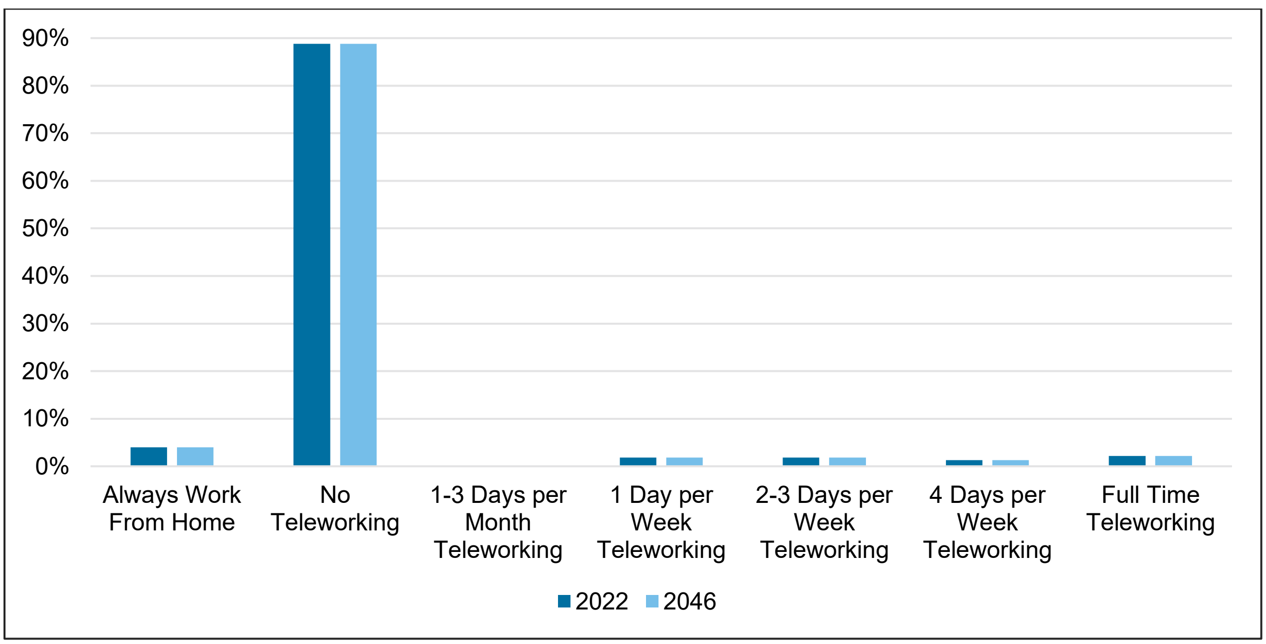
VARIABLE	2022	2046
MixedWorkFromHome	4.0%	4.0%
MixedNoTelework	88.3%	88.3%
MixedTelework1to3DaysPerMonth	0.1%	0.1%
MixedTelework1DayPerWeek	1.9%	1.9%

MixedTelework2to3DaysPerWeek	1.9%	1.9%
MixedTelework4DaysPerWeek	1.3%	1.3%
MixedTelework5DaysPerWeek	2.3%	2.3%
OnSiteWorkFromHome	4.0%	4.0%
OnSiteNoTelework	91.3%	91.3%
OnSiteTelework1to3DaysPerMonth	0.1%	0.1%
OnSiteTelework1DayPerWeek	1.1%	1.1%
OnSiteTelework2to3DaysPerWeek	1.1%	1.1%
OnSiteTelework4DaysPerWeek	0.8%	0.8%
OnSiteTelework5DaysPerWeek	1.4%	1.4%
RemoteWorkFromHome	4.0%	4.0%
RemoteNoTelework	86.5%	86.5%
RemoteTelework1to3DaysPerMonth	0.1%	0.1%
RemoteTelework1DayPerWeek	2.4%	2.4%
RemoteTelework2to3DaysPerWeek	2.4%	2.4%
RemoteTelework4DaysPerWeek	1.7%	1.7%
RemoteTelework5DaysPerWeek	2.9%	2.9%

Data valid as of 10.21.25

The work type distribution appears in Figure 23~~Figure 23~~.

FIGURE 23: PROPENSITY TO TELEWORK



Data valid as of 10.21.25

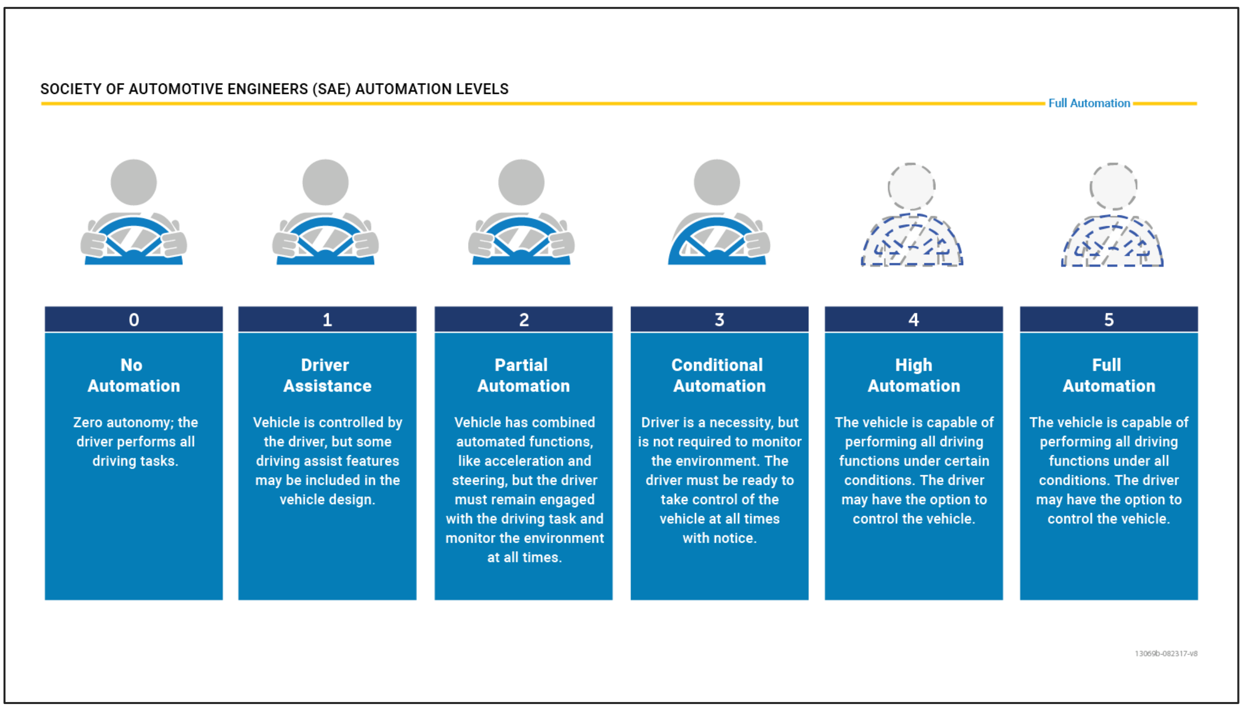
units.csv

This file describes the default units to be used for storing complex data types in the model. The VisionEval model system keeps track of the types and units of measure of all data that is processed. This file should not be modified.

Connected and Automated Vehicle Inputs

The VE model has been updated to account for highly automated vehicles including highly connected vehicles (Level 3) and fully self-driving vehicles (Level 5).

FIGURE 24: SAE LEVELS OF AUTOMATION (SOURCE: NHTSA)



The prototype model assigns vehicles one of three automation levels that align with the Society of Automotive Engineers' (SAE) levels of automation (Figure 24~~Figure 24~~):

- Level 0 (L0): No automation (human driver assumed)
- Level 3 (L3): Conditional automation (human driver assumed). The L3 vehicles are assumed to have the ability for cooperative cruise control, communication with traffic signals, and other V2X instances, but will require humans at the wheel and attentive.

- Level 5 (L5): Full automation (no human driver assumed). The L5 is a fully automated vehicle, providing no need for a human at the steering wheel for the trip. The L5 could operate as a ZOV, avoiding parking and returning to shuttle other occupants.

These inputs are for optional use of connected and automated vehicle investments or policies.

- **region_av_lev5_parameter/ region_driverless_vehicle_par**: changes in travel time utility (or disbenefits of travel time), how Level 5 vehicles can be remotely accessed, and whether they can avoid parking fees. The reference model assumes no L5 vehicles are available. Therefore, there are no values for these inputs.
- **region_av_lev5_propensity_coe**: This model uses household characteristics found in VE to determine a binary flag as to whether the household would be likely or interested in a Level 5 automated vehicle (if it were available). Table 55~~Table 55~~ shows a snapshot of the file with the following variables:
    - Constant
    - Fraction of adults 20 to 29 age band in the household
    - Fraction of adults 55 to 64 age band in the household
    - Fraction of adults over 65 age band in the household
    - LN Log for 1+ sum (number of kids ages 0 to 19) in the household
    - Income under 50k: 1 if the household income is <50k
    - Income above 100k: 1 if the household income is <100k
    - Total commute distance (or called distance to work) (limited to VERSPM)

TABLE 55: REGION_AV_LEV5_PROPENSITY_COEF.CSV INPUT FILE

YEAR	AVCONSTANT	AVFRACAGE20TO29COEF	AVFRACAGE55TO64COEF	AVFRACAGE65PCOEF	AVKIDSCOEF	AVHHINCBELOW50KCOEF	AVHHINCABOCE100KCOEF	AVDISTTOWRKCOEF
2022	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2046	-1.50	0.50	-0.50	-1.00	0.25	-0.50	1.00	0.01

Data valid as of 10.21.25

This new model allows the user to use the suggested defaults for the new coefficients or change the coefficients to change the level of L5 demand among the model households. Creating the coefficients as model inputs provides the user specific insight on how characteristics for L5 interest could evolve over time. For example, age cohort effects may not remain stable over the years that are included in the model.

Households flagged as having a high propensity to own or use a L5 vehicle may also own fewer vehicles given that a single L5 vehicle may satisfy the mobility needs more than a traditional human driven vehicle.

- **region_av_market_share.csv**: The share of Level 3 and Level 5 vehicles available for use in the model. The reference model asserts that by 2050, 60% of vehicles will have a high level of connectivity (Level 3), but no assumptions on fully autonomous Level 5 vehicles.

TABLE 56: REGION AV MARKET SHARE

YEAR	AVLVL0 SHARE	AVLVL3 SHARE	AVLVL5 SHARE
2022	99%	1%	0%
2046	40%	60%	0%

Data valid as of 9.29.25

- **region_car_svc_propensity_coef.csv**: This model uses the household demographic characteristics to determine a binary flag as to the household's interest in using shared modes. This would increase the likelihood of using shared modes and car service modes and may reduce vehicle ownership. The reference model did assume a general increase in interest by 2050. The following variables are used in the input file:
  - Constant
  - Fraction of adults 20 to 29 age band in the household
  - Fraction of adults 55 to 64 age band in the household
  - Fraction of adults over 65 age band in the household
  - Low car service level: 1 if the car service availability is low, 0 if high
  - Income under 50k: 1 if the household income is < 50k
  - Income above 100k: 1 if the household income is < 100k
  - D1B Population Density: rural density

TABLE 57: REGION CAR SVC PROPENSITY COEFFICIENT

YEAR	CSCONSTANT	CSFRACAGE20TO29COEF	CSFRACAGE55TO64COEF	CSFRACAGE65PCOEF	CSLOWCARSVCFLAGCOEF	CSHHINCBELOW50KFLAGCOEF	CSHHINCABOVE100KFLAGCOEF	CSD1BCOEF
2022	-0.5	0.5	-0.5	-1	-1.5	0.25	-0.25	0.0002
2046	-0.5	0.5	-0.5	-1	-1.5	0.25	-0.25	0.0002

Data valid as of 8.25.25

A household flagged as having a high propensity for shared car services are more likely to own fewer vehicles relative to other households.

- **region_driverless_vehicle_prop.csv**: This file asserts the share of Level 5 vehicles among car service, commercial service, vans, and buses. The reference model assumes all years have 0% Level 5 vehicle share.
- **av_lev5_effectiveness.csv**: the quantified maximum benefit in seconds of delay on freeway and arterials at different congestion levels associated with connected or automated vehicle types. This input defines the percent reduction in delay for a 100% market penetration rate (MPR) of AV level 5 vehicles. This allows users to define the reduction in delay by VisionEval's five congestion levels (none, moderate, heavy, severe, and extreme) as well as by roadway classification (freeway and arterial) and whether the congestion is non-recurring or recurring. This file has been created using average travel times for a completely automated fleet at different congestion levels. Fundamentally, day-to-day arterial operation is expected to see slower speeds at low levels of congestion due to behaviors of following speed limits and larger headways between vehicles in the traffic flow. Thus, there are negative values (-) shown in the table.

TABLE 58: AV_LEV5_EFFECTIVENESS.CSV INPUT FILE

LEVEL	ART_RCR	ART_NONRCR	FWY_RCR	FWY_NONRCR
None	100	100	100	100
Mod	100	-256.84	75	75
Hvy	47.42	-32.03	75	75
Sev	51.9	15.44	75	75
Ext	51.08	47.04	75	75

Data valid as of 8.15.25

- **marea_av_capacity_factors.csv**: changes in the roadway capacity to freeways or arterials based on the market penetration of the vehicle type. The data uses HCM research on CAVs as to the changes in capacity by facility type based on the share of highly automated vehicles.

The input allows users to define capacity factors that apply a multiplier to increase or decrease the lane miles for freeways and arterials in specific metro areas based on the MPR of L3 and L5 AVs. Much like the congestion tables, the model uses a lookup function to compare the specific metro areas and the share of VMT to allocate to various congestion levels based on the share of L3/L5 VMT to the overall VMT. These values are equal across all Mareas.

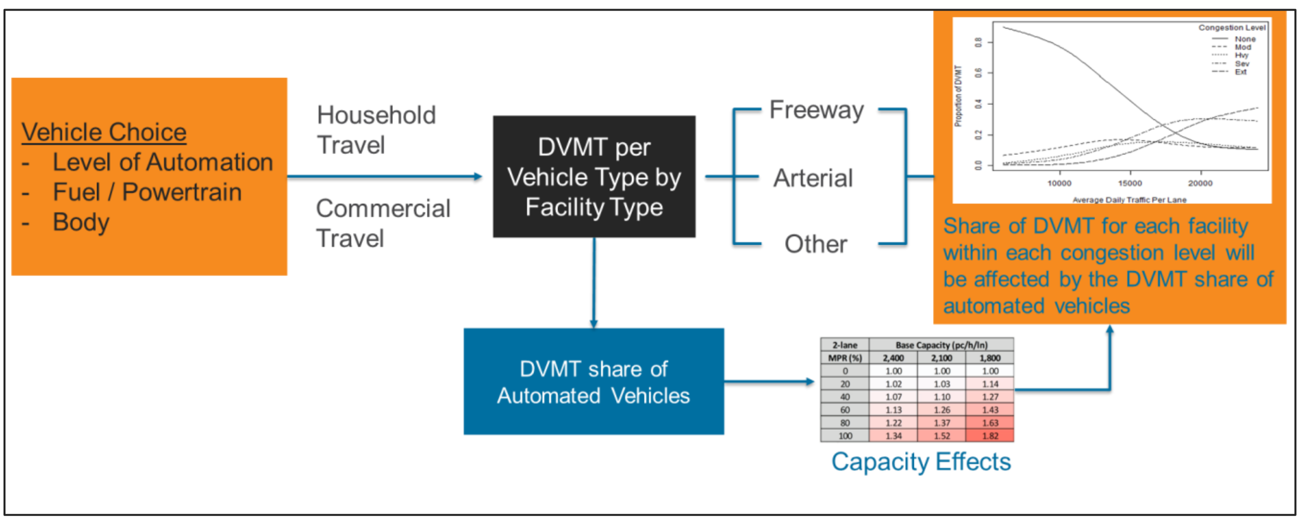
TABLE 59: NEW MAREA_AV_CAPACITY_FACTORS.CSV INPUT FILE

MPR	FWYCAPACITYMULTIPLIER	ARTCAPACITYMULTIPLIER
0	1	1
0.2	1.04	1
0.4	1.15	1
0.6	1.3	1
0.8	1.45	1.01
1	1.54	1.01

Data valid as of 8.25.25

The capacity increases for freeways and arterials are related to the DVMT share of CV/AVs and the magnitude to which CV/AVs will affect overall capacity. The DVMT share is a function of the upstream demand for automated vehicles at the household level. These capacity adjustments of CVs/AVs subsequently impact how the model splits light-duty vehicle DVMT between freeways and arterials. The relationship between all of these steps is shown in Figure 25~~Figure 25~~.

FIGURE 25: CAPACITY FLOW CHART



- **av_lev5_effect_adj_param.csv/ driverless_effect_adj_param.csv:** Parameters that change the slope and effect on recurrent vs non-recurrent delay. The parameters govern the delay and speed impacts driverless vehicles have based on the share of driverless vehicles in the overall vehicle fleet. The input adjusts values for the delay and speed smoothing by applying a function based on the proportion of DVMT that is driverless (L5 AVs only). The speed smoothing and delay values are initially calculated using other model inputs in the *other_ops_effectiveness.csv* and *marea_speed_smooth_ecodrive.csv* files. The model applies a function that adjusts those values based on the calculated proportion of DVMT that is driverless. The form of this function is:

$$DELAY = MAXDELAY * PROPDRIVERLESSDVMT^{BETA}$$

Where:

- MAXDELAY = delay assuming 100% driverless DVMT
- PROPDRIVERLESSDVMT = proportion of DVMT that is in L5 AV vehicles
- BETA = exponential smoothing parameter

If BETA has a value of 1, the relationship is linear. The higher the value of BETA, the less the incremental effect at lower driverless DVMT proportions and the greater the effect at higher driverless DVMT proportions, as shown in Figure 26~~Figure 26~~.

FIGURE 26: BETA EXPONENTIAL SMOOTHING PARAMETER

	Beta									
PropDriverless Dvmt	1	2	3	4	5	6	7	8	9	10
0	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
0.1	10.000%	1.000%	0.100%	0.010%	0.001%	0.000%	0.000%	0.000%	0.000%	0.000%
0.2	20.000%	4.000%	0.800%	0.160%	0.032%	0.006%	0.001%	0.000%	0.000%	0.000%
0.3	30.000%	9.000%	2.700%	0.810%	0.243%	0.073%	0.022%	0.007%	0.002%	0.001%
0.4	40.000%	16.000%	6.400%	2.560%	1.024%	0.410%	0.164%	0.066%	0.026%	0.010%
0.5	50.000%	25.000%	12.500%	6.250%	3.125%	1.563%	0.781%	0.391%	0.195%	0.098%
0.6	60.000%	36.000%	21.600%	12.960%	7.776%	4.666%	2.799%	1.680%	1.008%	0.605%
0.7	70.000%	49.000%	34.300%	24.010%	16.807%	11.765%	8.235%	5.765%	4.035%	2.825%
0.8	80.000%	64.000%	51.200%	40.960%	32.768%	26.214%	20.972%	16.777%	13.422%	10.737%
0.9	90.000%	81.000%	72.900%	65.610%	59.049%	53.144%	47.830%	43.047%	38.742%	34.868%
1	1	1	1	1	1	1	1	1	1	1

The value of BETA is defined in the input file *av_lev5_effect_adj_param.csv*, pictured in Table 60~~Table 60~~, for the recurring and non-recurring delay and smoothing by roadway classification.

TABLE 60: AV_LEV5_EFFECT_ADJ_PARAM.CSV INPUT FILE

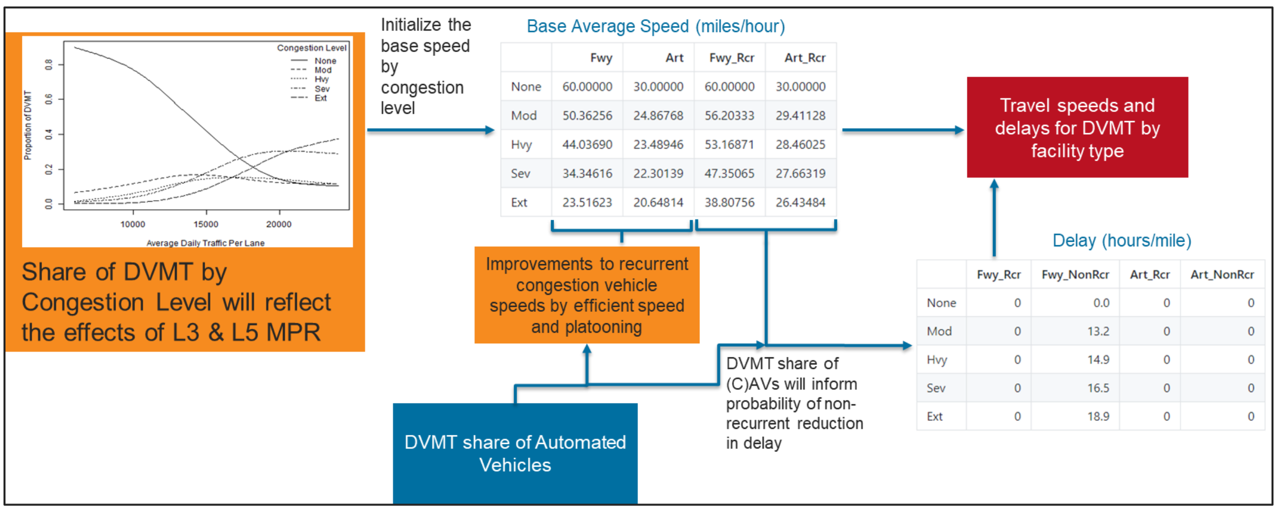
MEASURE	BETA
FwyRcrDelay	8
ArtRcrDelay	10
FwyNonRcrDelay	3

ArtNonRcrDelay	3
FwySmooth	5
ArtSmooth	7

Data valid as of 8.25.25

Figure 27Figure 27 visualizes how all the new capacity and congestion adjustment steps come together in VisionEval.

FIGURE 27: CAPACITY EFFECTS DUE TO RECURRENT AND NON-RECURRENT CONGESTION



2.4 REFERENCE MODEL RESULTS

The following tables and charts present the 2022 base year and 2046 future year results using the Population Sim version of the reference model. Table 61Table 61 shows the regional results for the reference scenario of the San Joaquin Valley model. The reference scenario suggests a 14.5% increase in vehicle trips per capita and a 13.8% increase in daily VMT per capita. Use of active transit modes marginally varies, with vehicle travel still being the predominant mode of transportation.

TABLE 61: BASE MODEL RESULTS – MODEL REGION

OUTPUT	2022	2046	PERCENT CHANGE
DVMT per capita	17.1	19.4	13.8%
Vehicle cost per mile (Household vehicles)	$ 0.69	$ 0.66	-5.4%
Daily CO2e per capita (kg/day, household travel)	5.9	0.13	-97.8%
Daily vehicle trips per capita	1.91	2.19	14.5%

Daily bike trips per capita	0.028	0.028	0.6%
Daily walk trips per capita	0.34	0.32	-6.1%
Daily transit trips per capita	0.21	0.18	-13.9%
Vehicles per household	2.10	2.05	-2.7%

TABLE 62: BASE MODEL – DVMT PER CAPITA BY MAREA

MAREA	2022	2046	PERCENT CHANGE
FCOG	15.4	16.4	6.8%
KCAG	17.2	18.1	5.4%
KCOG	16.2	20.2	24.6%
MCAG	17.1	21.0	22.2%
MCTC	19.2	19.9	3.9%
SJCOG	19.5	21.9	11.9%
StanCOG	17.7	19.3	9.1%
TCAG	16.7	19.6	17.2%

To ensure that the model closely matches true travel conditions in the model region, the reference model results for the base year are extracted and compared to empirical data sources. This provides some confidence that variations in local and state actions will closely match the desired effects on travel behavior.

Daily VMT (DVMT) is the primary VisionEval performance metric used to evaluate changes in travel behavior. To verify the accuracy of the VisionEval results, DVMT per household outputs were compared to empirical data sources, namely the 2022 San Joaquin Valley Household Travel Survey, from which RSG estimated DVMT per household by Azone, Marea, and model region. This comparison shows that VisionEval is estimating VMT in the San Joaquin Valley region within an average error of 2.8%, which closely matches travel behavior detailed in the Household Travel Survey.

TABLE 63: REFERENCE MODEL HOUSEHOLD DVMT VALIDATION

MAREA	YEAR	DVMT PER HH - HTS	DVMT PER HH - VE	DIFFERENCE	PERCENT DIFFERENCE
FCOG	2022	46.3	48.5	-2.2	-4.5%
KCAG	2022	53.0	50.4	2.5	5.0%
KCOG	2022	51.4	50.2	1.2	2.5%
MCAG	2022	63.7	55.8	7.9	14.1%
MCTC	2022	69.4	59.5	9.9	16.7%
SJCOG	2022	54.7	60.3	-5.6	-9.3%
STANCOG	2022	48.7	53.4	-4.7	-8.7%
TCAG	2022	53.6	50.9	2.8	5.4%
MODEL	**2022**	**55.1**	**53.6**	**1.5**	**2.8%**

2.5 VISIONEVAL RESULTS

VisionEval includes standard functions to export the results from any model. The default export produces CSV files for hundreds of standard performance measures, but alternative function parameters can export data in other formats including SQL. Results are provided at the Bzone, Azone, Marea, Region, household, person, worker and vehicle levels. Metadata is provided for all variables, including description, units, source table, and input sources.

Exporting Results

VisionEval includes a simple R command-line interface for running models and extracting results. When results are exported using the commands below, a series of CSV files or a SQLite database is created and saved in the "results" folder.

```
model <- openModel("VERSPM-base")
model$run()
results <- model$results()
# To export to csv
results$export()
# To export to SQLite
results$export("sql")
```

Querying Results

VisionEval includes a built-in query function that allows users to summarize data from the exported SQLite database. Documentation on the query function can be found in the Full-Query.VEqry file saved in a model's "queries" folder. The file describes query parameters and syntax and provides numerous examples.

A .VEqry file is a query object that contains a list of individual queries. Each individual query itself is a list containing the following elements:

- "Name": name of query or measure
- "Summarize" or "Function":
  - If using "Function", define a string containing an R expression
  - If using "Summarize", a list, define the following:
    - "Expr" (required): the summarize variable expression
    - "Units" (required): for each variable referred to in "Expr" or "By", the units of the corresponding variable

  - "By": A vector of variables along which to break out a Measure
  - "Table": A vector of one or more tables that will be joined
  - "Breaks" (optional): used to turn numeric variables into categories
  - "BreakNames" (optional): Nice names to append to the Breaks
  - "Key" (optional): (if Table contains more than one Table) – the variable or field in all listed Tables to join by
- "Units": output units in which the measure is expressed
- "Description": description of the measure

Figure 28~~Figure 28~~ shows an example of a query.

FIGURE 28: EXAMPLE QUERY

```
QuerySpec <- list(

  #### DVMT
  #TotalDVMT
  #--------------------
  list(
    Name = "TotalDvmt",
    Summarize = list(
      Expr = "sum(Dvmt)",
      Units = c(
        Dvmt = "MI/DAY",
        Marea = ""
      ),
      By = "Marea",
      Table = "Household"
    ),
    Units = "Miles per day",
    Description = "Total daily vehicle miles traveled by households by Marea"
  )
)
```

After a .VEqry file has been created to perform the desired summaries and saved in the "queries" folder, it can be run in the R as shown below. The results of the query will be saved in a .Rda file in the "results" folder.

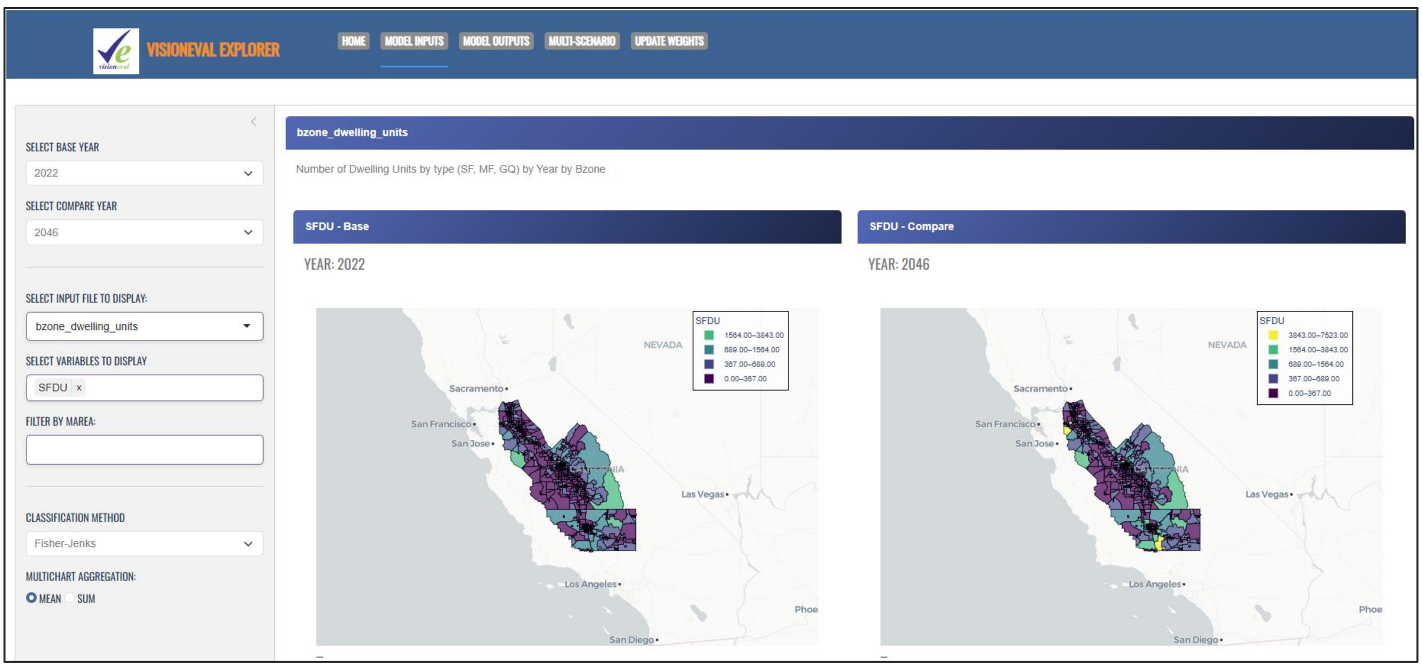
```
# After running model
model <- model$openModel("VERSPM-base")
query <- model$query("name-of-query")
query$run()
query$export()
```

A software option available to improve the visibility of VisionEval inputs and outputs is the VisionEval Explorer developed by RSG. The VisionEval Explorer is a dashboard designed in the Shiny software to assist users in visualizing model inputs and outputs.[37] It can be utilized for input quality control, output visualization, and analysis of multiscenario model runs.

Explorer: Model Input Visualizer

The Input Visualizer in the Explorer allows users to examine how specific model input values differ across model years and geographies. The visualizer will produce charts and maps that can be manipulated by the user to more closely examine specific inputs. To examine a specific input and compare model years, users can choose the model base year, a comparison year, a specific input file, and the input fields they would like to visualize. This will generate either maps or charts of a specific input field. Additional options include filtering the inputs by Marea, adjusting the classification method, or examining either aggregated or averaged inputs.

FIGURE 29: BZONE_DWELLING_UNITS VISUALIZATION EXAMPLE



Explorer: Model Output Visualizer

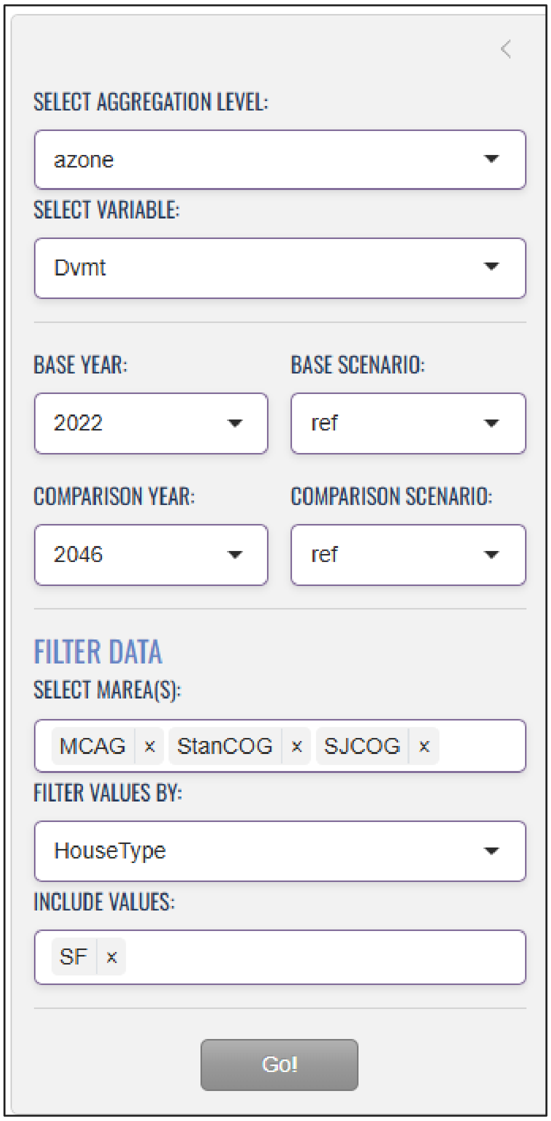
The Output Visualizer allows users to examine how calculated model outputs vary across model years and geographies. Similar to the Input Visualizer, this tab will produce charts and maps of specific output measures that can be used to assess key model outputs and performance. This dashboard includes the following fields:

[37] rsginc.shinyapps.io/visioneval-explorer-sjv/

- **Aggregation level:** This dropdown menu allows users to select the aggregation geography at which they would like to view a specified output (ex. Number of households at the Marea level). Note that some outputs produced at higher level geographies cannot be viewed at lower levels – an output produced at the Marea level cannot be aggregated to Bzones.
- **Variable selection:** Users can select the output they would like to visualize.
- **Base year:** The base year of the model.
- **Comparison year:** The year the user would like to compare to the base year. This includes all model results.
- **Select Marea(s):** This field allows users to filter results to specific Mareas in the model geography. Multiple Mareas can be selected.
- **Filter values by:** This field allows users to filter results by non-geographic segmentation. For example, the field “HouseType” allows users to filter model results by dwelling unit type (single family, multifamily, or group quarters dwelling units).
- **Include values:** This field specifies the values used for segmentation. For example, users can use this menu to select which household types they would like to visualize.

Click “Go” once all selections are complete to visualize the results with the selected filters.

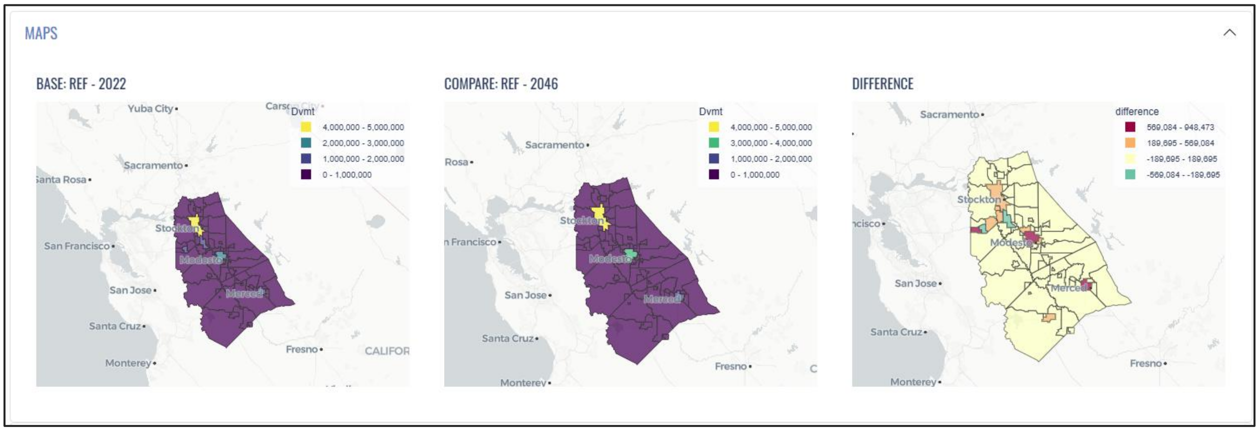
FIGURE 30: OUTPUT VISUALIZER MENU – AZONE DVMT FOR SINGLE FAMILY HOUSEHOLDS IN SJCOG, STANCOG, AND MCAG MAREAS



This selection will produce a series of visuals for users to inspect:

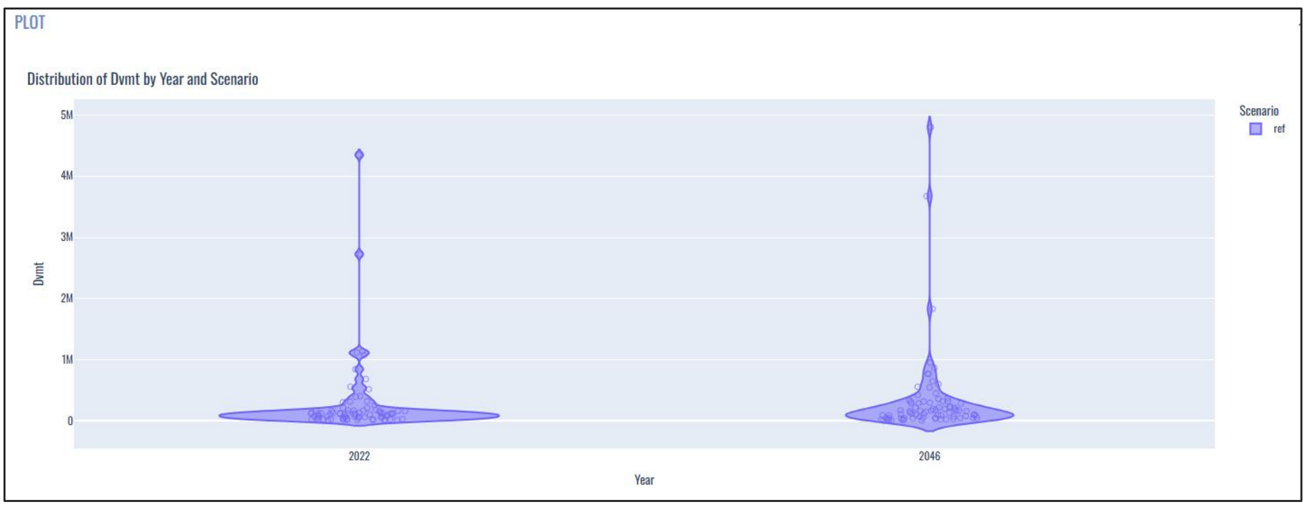
- **Maps:** This tab will produce three maps specified using the filters in Output Visualizer Menu. The maps include outputs for the selected base year, outputs for the comparison year, and the differences between the two maps.

FIGURE 31: OUTPUT VISUALIZER OUTPUT – MAPS



- **Plot:** This plot represents the distribution of filtered output values for each model year. In Figure 32~~Figure 31~~, the plot shows the distribution of DVMT values at the Azones level within the SJCOG, StanCOG, and MCAG Mareas for the selected model years.

FIGURE 32: OUTPUT VISUALIZER OUTPUT – PLOT



- **Summary Table:** A filtered tabular output for each geography included in the maps.

FIGURE 33: OUTPUT VISUALIZER OUTPUT – SUMMARY TABLE

SUMMARY TABLE

azone	n_ref_2022	n_ref_2046	Dvmt_ref_2022	Dvmt_ref_2046
1	5642	2805	262351.1606326277	152179.19947299198
4	5907	3132	316025.9801395696	195419.5471063112
5	1492	1768	78168.30824550756	98416.02122209546
8	1218	1770	57828.86599438521	82902.5679847886
10	535	1652	27656.897491013206	98513.05407786054
13	1764	2605	124823.49559465426	187154.37975930332
16	2537	431	119294.19490467347	23742.395163318655
17	1964	3105	105193.71828711378	170344.065658272
19	2438	9760	125692.89123814204	450552.488732496
20	629	190	27601.76966438323	12015.498268844744
26	364	2221	23171.67842835633	168007.42343467352
28	2171	3825	116650.84031089631	215681.8913915071
31	10268	14216	559125.923061362	771676.3827005705
37	15020	14523	684607.2087423505	648158.1268255254
39	2522	2159	180203.31908750202	166400.02080075894
43	60435	77566	2724589.5356165203	3673062.800078957

Viewing rows 1 through 16 of 79

3.0 MULTISCENARIO ANALYSIS

3.1 BACKGROUND

The multiscenario analysis is designed to run hundreds of VisionEval models for the San Joaquin Valley region that combine unique changes to specific input values across several input types. This is referred to in VisionEval as the Multiscenario design. In this set up, users can substitute alternative values that may reflect a potential alternative future for the base-level inputs (i.e., the reference case inputs). This allows users to create model runs with more or less aggressive input values based on potential policy or pricing futures and compare their effects to the base scenario. For example, users could test how DVMT may be affected by higher investment in policies that improve active travel and transit mode shares in the model region or within a Marea. Decisions on which inputs to vary and how aggressively to test them should be informed by stakeholder input, potential policy goals, and existing plans.

3.2 INPUT DESIGN FOR THE MULTISCENARIO ANALYSIS

The tested scenarios were designed with feedback from MPO members of the San Joaquin Valley working group in collaboration with RSG. This feedback informed which inputs were varied and the relative scale of the variation. Several inputs were explored in the scenario analysis organized into categories, with multiple levels of change within each category. Each level represents a new degree of change to the reference model inputs. The various levels from each category were then combined to create the scenarios using unique combinations of these model inputs. The input variations resulted in 109 scenarios, not including the base model. All geographic data required to develop new land use inputs (ex. Transit oriented development areas) was provided by the San Joaquin Valley MPOs.

The categories and input levels used for the scenario analysis are shown in Table 64~~Table 64~~ and

Table 65~~Table 65~~.

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TABLE 64: SCENARIO CATEGORIES

CATEGORY NAME	DESCRIPTION
Population and Land Use (PLU)	Changes to land use and Population Sim inputs to represent new land use patterns. These inputs are grouped to be run together in specific combinations.
Fees / Costs (Fee)	Changes to pricing inputs that impact driving costs.

Travel Demand Management (TDM)	Instituting parking costs of $2 a day across all urban area Bzones within the model region.
Transportation Infrastructure (TI)	Changes to potential future investments that result in development of specific transportation infrastructure including changes in transit accessibility, propensity to use active travel modes, and increased lane miles (note increased lane miles was used in only one unique scenario).

TABLE 65: SCENARIO LEVELS (NOT INCLUDING REFERENCE INPUTS)

CATEGORY	LEVEL	DESCRIPTION	2050 VARIED INPUTS
Population (P)	1	2023 CA Dept. of Finance population forecast, use with reference-level land use only and hold household sizes fixed	VEPopulationSimInputs
	2	20% employment growth, use with reference-level land use only	bzone_employment.csv
	3	Population level 1, let household sizes vary	VEPopulationSimInputs
	4	2023 CA Dept. of Finance population forecast, use with land use level 1 only and hold household sizes fixed	VEPopulationSimInputs
	5	2023 CA Dept. of Finance population forecast, use with land use level 2 only and hold household sizes fixed	VEPopulationSimInputs
	6	2023 CA Dept. of Finance population forecast, use with land use level 3 only and hold household sizes fixed	VEPopulationSimInputs
Land Use (L)	1	Housing mix and TOD: Transit oriented development and 50% increase in multifamily dwelling unit share in urban areas. 20% increase in other areas.	bzone_dwelling_units.csv
	2	Compact growth: All housing and job growth isolated to only urbanized areas.	bzone_dwelling_units.csv

	3	Job-housing balance: Maintain a job to housing balance of 1 to 1.	bzone_dwelling_units.csv
Fees / Costs (F)	1	50 cents per mile congestion charge during periods of extreme or severe congestion.	marea_congestion_charges.csv
	2	Level 1 plus 2.5 cents VMT tax per mile.	marea_congestion_charges.csv, azone_veh_use_taxes.csv
Travel Demand Management (D)	1	Add a parking cost of $2 per day in all urbanized Bzones.	bzone_parking.csv
Transportation Infrastructure (T)	1	Increased transit infrastructure: Double transit service and accessibility	marea_transit_service.csv, bzone_transit_service.csv
	2	Active travel infrastructure: 50% increase in propensity to use active travel modes.	azone_prop_sov_dvmt_diverted.csv
	3	Road infrastructure: 50% increase in arterial lane miles	marea_lane_miles.csv

3.3 SCENARIO RESULTS

To view and interpret results from the scenarios, RSG applied the VisionEval Explorer described above to allow users to examine the impact of specific levers or uncertainties on various model outputs. This chapter will explain the key performance measures chosen from the model results and how to use the Explorer to compare these measures across scenarios.

Performance Measures

A series of performance measures were selected and extracted from each VisionEval scenario including the base models. These key metrics are then compared across scenarios. Table 66~~Table~~ includes the list of performance measures.

TABLE 66: PERFORMANCE MEASURES

PERFORMANCE MEASURES		
Transit trips	Transit trips per capita	Bike trips per capita
Bike trips	Walk trips	Walk trips per capita
Vehicle trips	Vehicle trips per capita	Average commute distance

Transit person miles traveled	Bike person miles traveled	Walk person miles traveled
Vehicle delay	Average congestion charges	Average vehicle cost per mile
Average congestion price per mile	Average road use tax per mile	Daily CO2 emissions
DVMT	DVMT per capita	Daily Bus CO2e
Daily Freeway VMT – Heavy Trucks	Daily Arterial VMT – Heavy Trucks	Daily fuel consumption (in gallons of gasoline equivalent)
Daily kilowatt hours consumed	ICEV (internal combustion engine) powertrain vehicles	HEV (hybrid) powertrain vehicles
PHEV (plug-in hybrid) powertrain vehicles	BEV (battery electric) powertrain vehicles	Number of teleworkers
Population		

Output Segmentation

Some performance measures are also segmented by household income or geography which allows users to see the impact of certain policies or plans on different populations within the model region. Income segmentation is done using the household income outputs for each individual household within the model region. These are divided into very low income households (<$45k annually), low income households ($45-75k annually), moderate income households ($75-120k annually), and high-income households (> $120k annually). The performance measures that are segmented by income are listed in Table 67~~Table 67~~ and are listed as separate outputs in the Multiscenario Viewer.

TABLE 67: INCOME SEGMENTED PEFORMANCE MEASURES

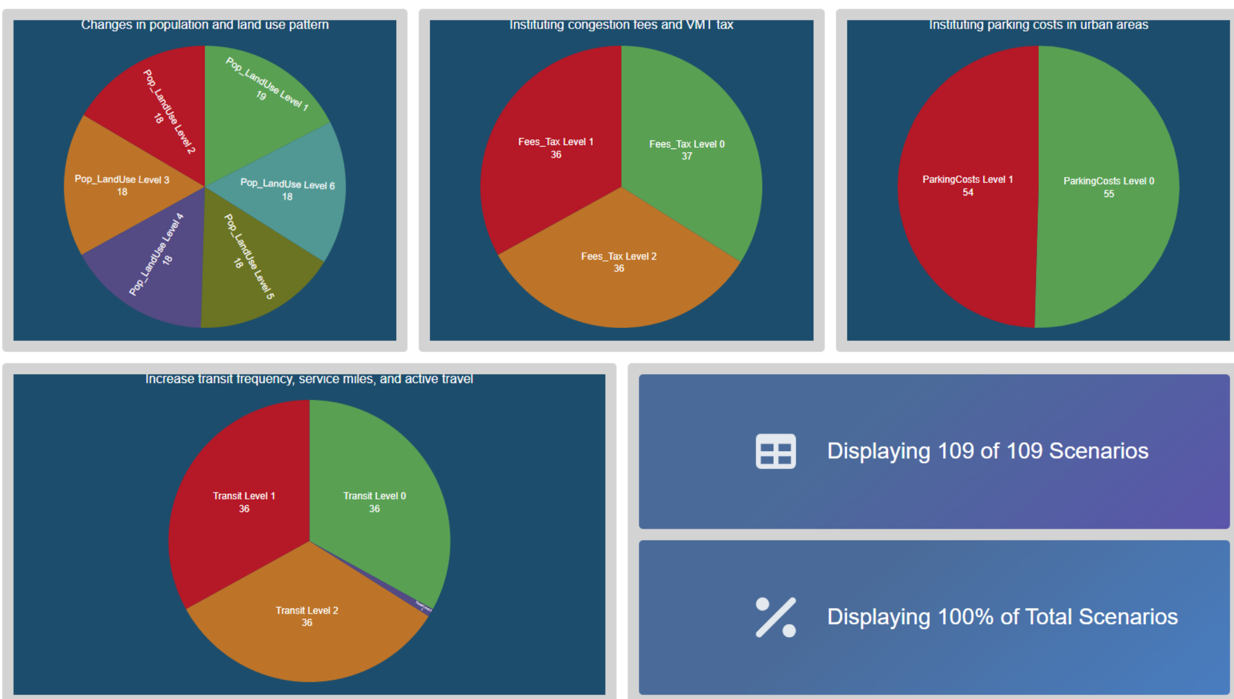
INCOME SEGMENTED PERFORMANCE MEASURES		
DVMT per capita – Very low income households	DVMT per capita – Low income households	DVMT per capita – Moderate income households
DVMT per capita – High income households	Average per mile vehicle cost – Very low income households	Average per mile vehicle cost – Low income households

Average per mile vehicle cost – Moderate income households	Average per mile vehicle cost – High income households

Explorer: Using the Multiscenario Viewer

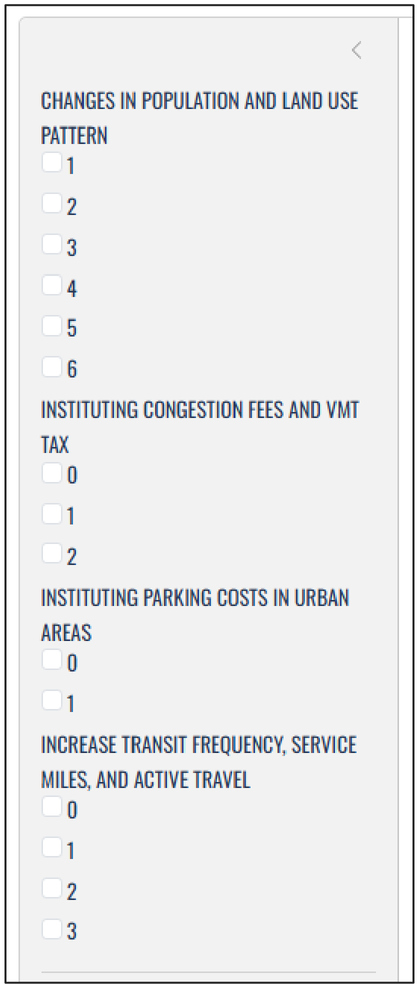
The Multiscenario Viewer is a dashboard within the VisionEval Explorer that allows users to examine results of the VisionEval multiscenario model runs.[38] Model results from each scenario are processed into a series of performance measures. Users can examine how these performance measures change for each level of input variation, and how many scenarios fall into each level using the "Multi-scenario" tab of the dashboard. The levels selection allows users to select which scenarios they want to visualize. For example, selecting "Changes in population and land use patterns" level 1 will filter the results to those from model runs using these level 1 input values. Level 0 inputs are those used in the reference model.

FIGURE 34: MULTISCENARIO VIEWER SCENARIOS DISPLAY



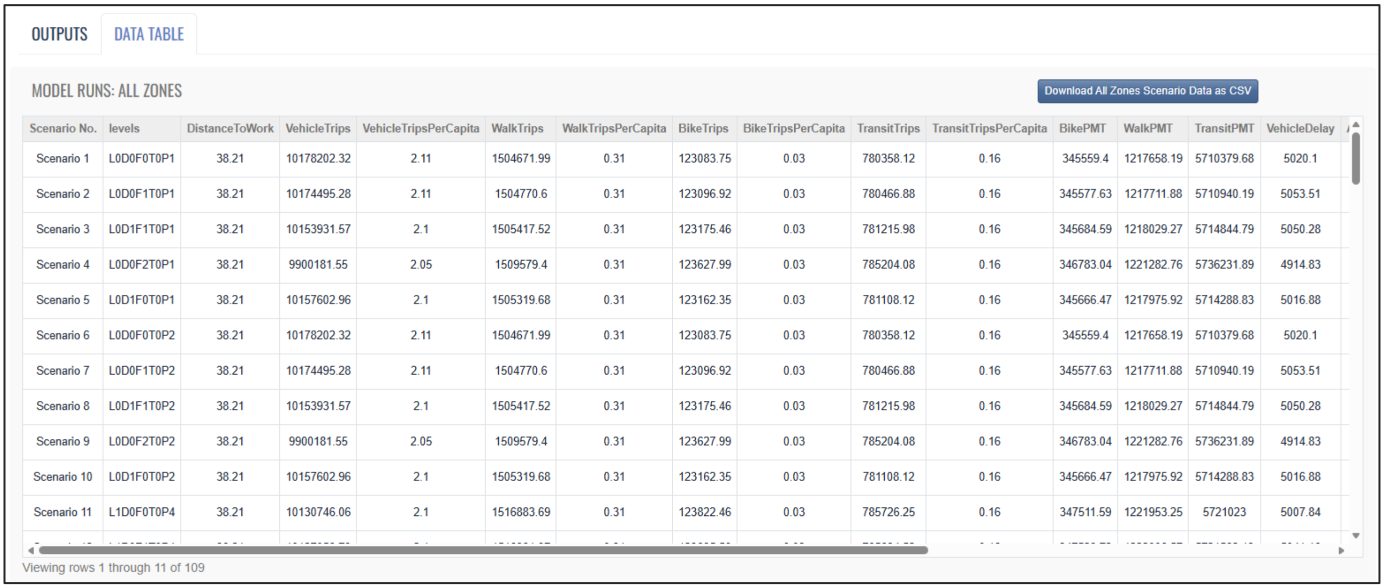
38 rsginc.shinyapps.io/visioneval-explorer-sjv/

FIGURE 35: MULTISCENARIO VIEWER LEVELS SELECTION



The "Data Table" shows a table of all scenario results and allows users to download a CSV file of individual scenario results for the future model year.

FIGURE 36: MULTISCENARIO VIEWER – DATA DISPLAY



OUTPUTS DATA TABLE

MODEL RUNS: ALL ZONES

Download All Zones Scenario Data as CSV

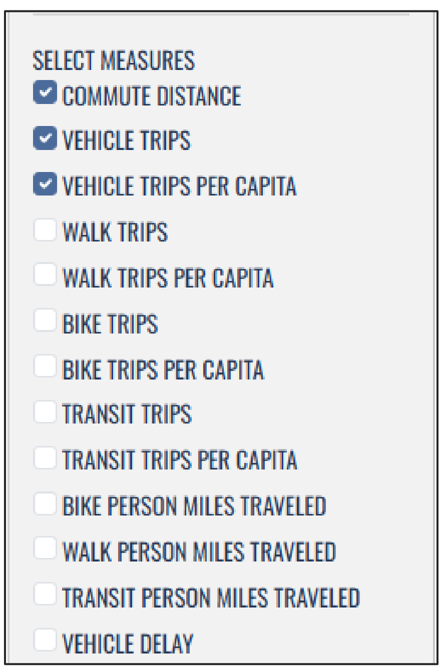
Scenario No.	levels	DistanceToWork	VehicleTrips	VehicleTripsPerCapita	WalkTrips	WalkTripsPerCapita	BikeTrips	BikeTripsPerCapita	TransitTrips	TransitTripsPerCapita	BikePMT	WalkPMT	TransitPMT	VehicleDelay
Scenario 1	L0D0F0T0P1	38.21	10178202.32	2.11	1504671.99	0.31	123083.75	0.03	780358.12	0.16	345559.4	1217658.19	5710379.68	5020.1
Scenario 2	L0D0F1T0P1	38.21	10174495.28	2.11	1504770.6	0.31	123096.92	0.03	780466.88	0.16	345577.63	1217711.88	5710940.19	5053.51
Scenario 3	L0D1F1T0P1	38.21	10153931.57	2.1	1505417.52	0.31	123175.46	0.03	781215.98	0.16	345684.59	1218029.27	5714844.79	5050.28
Scenario 4	L0D0F2T0P1	38.21	9900181.55	2.05	1509579.4	0.31	123627.99	0.03	785204.08	0.16	346783.04	1221282.76	5736231.89	4914.83
Scenario 5	L0D1F0T0P1	38.21	10157602.96	2.1	1505319.68	0.31	123162.35	0.03	781108.12	0.16	345666.47	1217975.92	5714288.83	5016.88
Scenario 6	L0D0F0T0P2	38.21	10178202.32	2.11	1504671.99	0.31	123083.75	0.03	780358.12	0.16	345559.4	1217658.19	5710379.68	5020.1
Scenario 7	L0D0F1T0P2	38.21	10174495.28	2.11	1504770.6	0.31	123096.92	0.03	780466.88	0.16	345577.63	1217711.88	5710940.19	5053.51
Scenario 8	L0D1F1T0P2	38.21	10153931.57	2.1	1505417.52	0.31	123175.46	0.03	781215.98	0.16	345684.59	1218029.27	5714844.79	5050.28
Scenario 9	L0D0F2T0P2	38.21	9900181.55	2.05	1509579.4	0.31	123627.99	0.03	785204.08	0.16	346783.04	1221282.76	5736231.89	4914.83
Scenario 10	L0D1F0T0P2	38.21	10157602.96	2.1	1505319.68	0.31	123162.35	0.03	781108.12	0.16	345666.47	1217975.92	5714288.83	5016.88
Scenario 11	L1D0F0T0P4	38.21	10130746.06	2.1	1516883.69	0.31	123822.46	0.03	785726.25	0.16	347511.59	1221953.25	5721023	5007.84

Viewing rows 1 through 11 of 109

Viewing Performance Measures

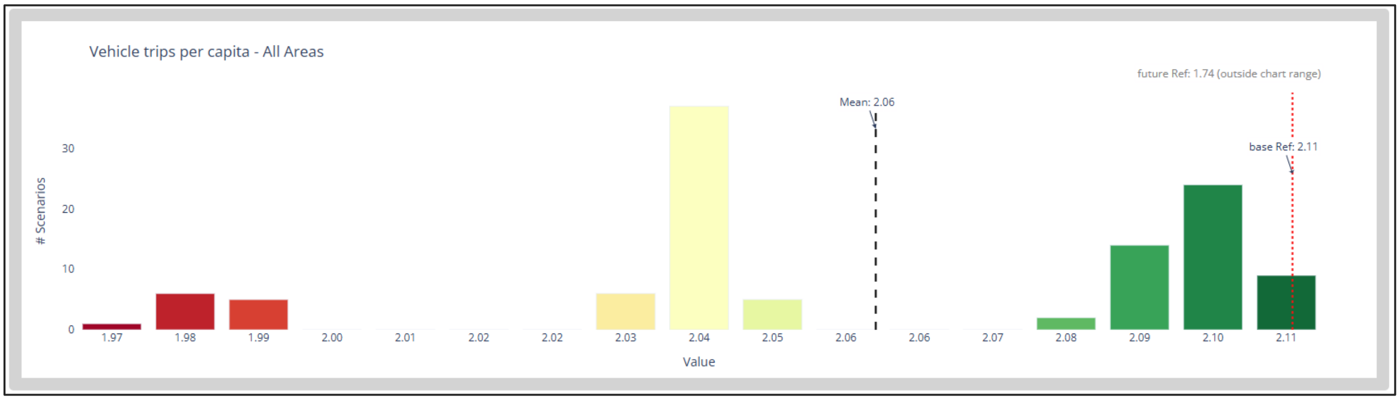
Users can also toggle which performance metrics are displayed using the sidebar menu of the dashboard. This will list all the performance measures extracted from the model results. Multiple measures can be selected and displayed at once.

FIGURE 37: PERFORMANCE MEASURES MENU



When a performance measure is selected, a histogram will populate showing the range of possible outcomes for this output. Users can select a combination of input levels and performance measures to display a set of results from a particular set of scenarios that reflect the selected level of input values. The Y-axis of the resulting bar chart shows a count of the number of scenarios, and the X-axis represents the values of the performance measure. This chart helps users understand where performance measure values are concentrated in the selected scenarios.

FIGURE 38: SCENARIO RESULTS SAMPLE

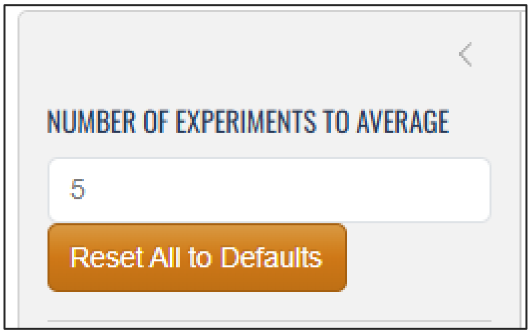


Explorer: Using the Weighted Output Explorer

The Weighted Output Explorer under the “Update Weights” tab of the VisionEval Explorer allows users to understand which model scenarios best fit their regional goals. Each scenario is assigned a score based on the percentile of its output value in comparison to the rest of the model runs (ex. The scenarios with the lowest DVMT will be the lowest percentile values for DVMT). This dashboard will assess the selected weights and directionality, choose which scenarios best fit the weights based on these percentiles, and then average the outputs across a specified number of selected “best fit” scenarios.

To start, users can select how many scenarios they would like to average. This menu will specify how many of the “best fit” scenarios will be selected. In this case, the dashboard is selecting the top five scenarios.

FIGURE 39: NUMBER OF EXPERIMENTS TO AVERAGE



Next, users can select a specific variable they would like to observe in the selected scenarios. This will generate a bar chart showing the average values for that particular output in the “best fit” scenarios.

FIGURE 40: VARIABLE SELECTION

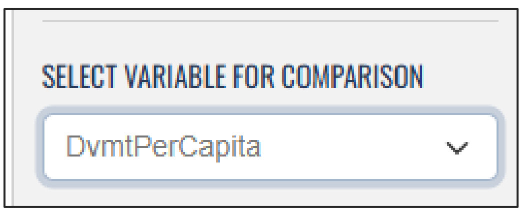
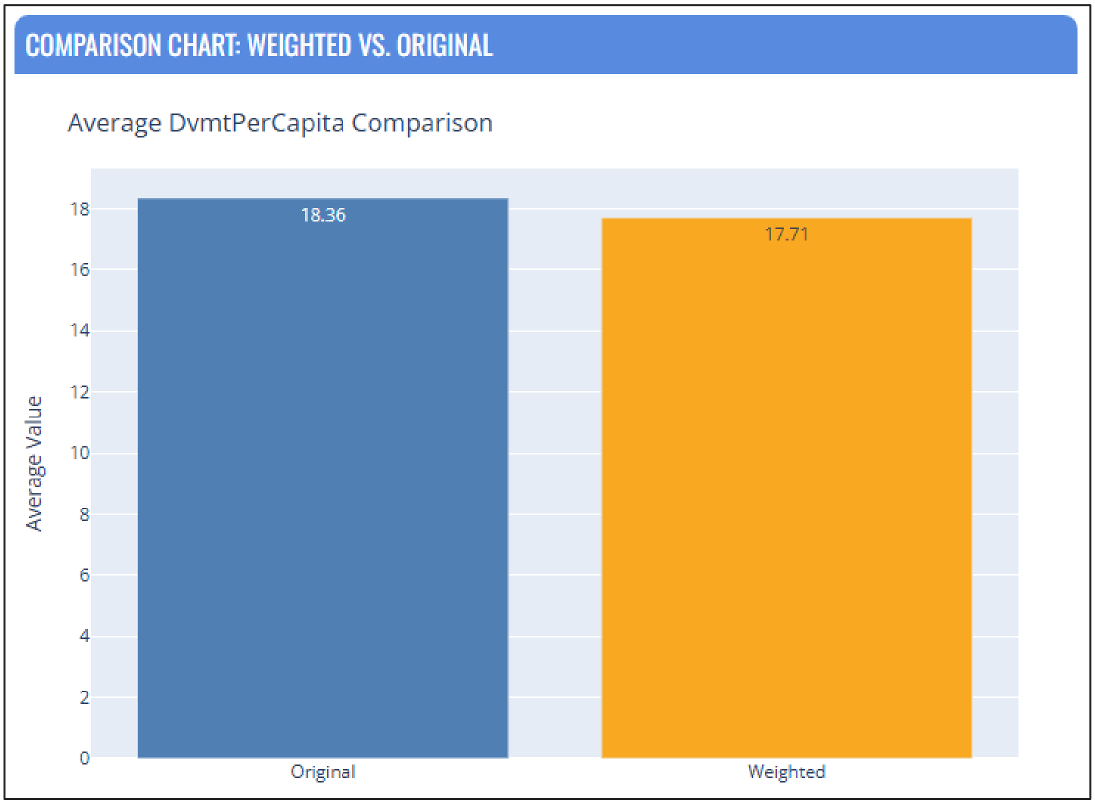


FIGURE 41: BAR CHART – SELECTED VARIABLE



Finally, users will assign weights to performance metrics by priority in the “Weight and Factor Input” section of the dashboard. The “Factor” determines the directionality of a performance measure. Measures that users will ideally want to reduce, such as DVMT and CO2e, should have a factor of -1, while measures that users want to increase, such as bike or walk trips, should have a factor of 1. This example will use the following weights:

TABLE 68: SAMPLE WEIGHTS

VARIABLE	WEIGHT	FACTOR
DVMT per capita	40	-1
Daily walk trips	20	1
Daily bike trips	20	1
Daily transit trips	20	1

FIGURE 42: SAMPLE WEIGHTS TABLE

WEIGHT AND FACTOR INPUT

Variable	Weight	Factor
Auto30Min_prcitle	0	1
Walk15Min_prcitle	0	1
Bike30Min_prcitle	0	1
Transit60Min_prcitle	0	1
Population_prcitle	0	1
HHs_prcitle	0	1
HhPropUrban_prcitle	0	1
HhPropTown_prcitle	0	1
HhPropRural_prcitle	0	-1
DvmtPerCapita_prcitle	40	-1
Dvmt_prcitle	0	1
DvmtPerCapita_VeryLowIncome_prcitle	0	1
DvmtPerCapita_LowIncome_prcitle	0	1
DvmtPerCapita_ModIncome_prcitle	0	1
DvmtPerCapita_HighIncome_prcitle	0	1
BikeTrips_prcitle	20	1
BikeTripsPerCapita_prcitle	0	1
BikeAvgTripDist_prcitle	0	1
BikePMT_prcitle	0	1
WalkTrips_prcitle	20	1

These weights will produce a score for each scenario that represents how well a scenario fits the criteria. These can be viewed in the "Score" field of the "Data Table" tab, which reflects the selected weights. These scores are used to filter to the specified number of "best fit" scenarios (ex. The dashboard will filter to the scenarios with the top five scores). These scored results can be downloaded as a CSV file from the "Data Table" tab. The sample table in Figure 43~~Figure 42~~ uses the weights specified in Table 68~~Table 68~~.

FIGURE 43: WEIGHTED OUTPUT – SCORED DATA TABLE SAMPLE

WEIGHTED SCORES BY ID

Download Data

ehCostPM_HighIncome_prcitle	BikeInjuryCrash_prcitle	AutoInjuryCrash_prcitle	AutoFatalCrash_prcitle	ArtTTI_prcitle	FwyTTI_prcitle	BikeInjuryCrashPC_prcitle	AutoInjuryCrashPC_prcitle	AutoFatalCrashPC_prcitle	Score
	0.3119266055045872	0.009174311926605505	0.009174311926605505	0.5045871559633028	0.5045871559633028	0.3119266055045872	0.009174311926605505	0.009174311926605505	0.1853
49541284403671	0.30275229357798167	0.01834862385321101	0.01834862385321101	0.5045871559633028	0.5045871559633028	0.30275229357798167	0.01834862385321101	0.01834862385321101	0.1761
9908256880734	0.9724770642201835	0.11926605504587157	0.11926605504587157	0.5045871559633028	0.5045871559633028	0.9724770642201835	0.11926605504587157	0.11926605504587157	0.1523
9816513761468	0.9633027522935781	0.12844036697247707	0.12844036697247707	0.5045871559633028	0.5045871559633028	0.9633027522935781	0.12844036697247707	0.12844036697247707	0.1468
07339449541286	0.9449541284403671	0.2018348623853211	0.1559633027522936	0.5045871559633028	0.5045871559633028	0.9449541284403671	0.2018348623853211	0.1559633027522936	0.1339
81651376146789	1	0.13761467889908258	0.13761467889908258	0.5045871559633028	0.5045871559633028	1	0.13761467889908258	0.13761467889908258	0.1101
65137614678899	0.724770642201835	0.14678899082568808	0.14678899082568808	0.5045871559633028	0.5045871559633028	0.724770642201835	0.14678899082568808	0.14678899082568808	0.1083
41284403669725	0.3302752293577982	0.02752293577981652	0.02752293577981652	0.5045871559633028	0.5045871559633028	0.3302752293577982	0.02752293577981652	0.02752293577981652	0.1083
06422018348624	0.9357798165137615	0.27522935779816515	0.21100917431192662	0.5045871559633028	0.5045871559633028	0.9357798165137615	0.27522935779816515	0.21100917431192662	0.1028
23853211009176	0.7706422018348624	0.17431192660550457	0.17431192660550457	0.5045871559633028	0.5045871559633028	0.7706422018348624	0.17431192660550457	0.17431192660550457	0.0954
23853211009176	0.7706422018348624	0.17431192660550457	0.17431192660550457	0.5045871559633028	0.5045871559633028	0.7706422018348624	0.17431192660550457	0.17431192660550457	0.0954
23853211009176	0.7706422018348624	0.17431192660550457	0.17431192660550457	0.5045871559633028	0.5045871559633028	0.7706422018348624	0.17431192660550457	0.17431192660550457	0.0954
08256880733946	0.1651376146788991	0.03669724770642202	0.03669724770642202	0.5045871559633028	0.5045871559633028	0.1651376146788991	0.03669724770642202	0.03669724770642202	0.0899
6422018348624	0.6880733944954129	0.22018348623853215	0.2018348623853211	0.5045871559633028	0.5045871559633028	0.6880733944954129	0.22018348623853215	0.2018348623853211	0.0716
90825688073394	0.3211009174311927	0.07339449541284404	0.07339449541284404	0.5045871559633028	0.5045871559633028	0.3211009174311927	0.07339449541284404	0.07339449541284404	0.0716
80733944954129	0.9908256880733946	0.21100917431192662	0.1926605504587156	0.5045871559633028	0.5045871559633028	0.9908256880733946	0.21100917431192662	0.1926605504587156	0.0661

Viewing rows 1 through 16 of 109

A table with the average output values in these scenarios will also be produced. This shows a full list of outputs included in the model outputs for the "best fit" scenarios.

FIGURE 44: WEIGHTED OUTPUT - AVERAGED VALUES

AVERAGE VALUES

Metric	Average
DistanceToWork	38.21
Auto30Min	1073049
Walk15Min	338956
Bike30Min	625831
Transit60Min	1022162
Population	4831668
HHs	1694172
HhPropUrban	0.64
HhPropTown	0.347
HhPropRural	0.013
DvmtPerCapita	17.928
Dvmt	86624353.85
DvmtPerCapita_VeryLowIncome	13.208
DvmtPerCapita_LowIncome	18.506
DvmtPerCapita_ModIncome	20.783
DvmtPerCapita_HighIncome	23.463

The “Policy Variable Summary Table” shows users the distribution of selected scenarios that meet the regional goals. These categories include those defined in the multiscenario analysis: Changes in Population and Land Use Patterns (PLU), Congestion Fees and VMT Taxes (Fees), Parking Costs (TDM), and Transportation Infrastructure (TI).

Figure 45~~Figure 44~~ shows that in the current example, to achieve the desired outcomes for DVMT and non-vehicle trips are best met by using a combination of PLU level 4, Fees level 2, TDM levels 0 or 1, and TI levels 1 or 2. This table allows users to effectively see what combination of the scenario levels specified in Table 65~~Table 65~~ best match specific policy goals or preferred futures.

FIGURE 45: POLICY VARIABLE SUMMARY

POLICY VARIABLE SUMMARY

Value	PLU	Fees	TDM	TI
0	0%	0%	40%	20%
1	0%	0%	60%	40%
2	0%	100%	0%	40%
3	0%	0%	0%	0%
4	100%	0%	0%	0%
5	0%	0%	0%	0%
6	0%	0%	0%	0%
Mean	4.0	2.0	0.6	1.2
No. of Experiments	5	5	5	5

APPENDIX A. REFERENCE POPULATION SIM OUTPUTS

TABLE 69: POPULATION SIM PERSONS INPUTS

MAREA	YEAR	POPULATION	0-14	15-19	20-29	30-54	55-64	65+	AVGPINC
FCOG	2022	1,053,956	232,168	76,361	147,767	331,319	114,698	151,643	$27,105
FCOG	2046	1,197,695	263,434	85,548	170,056	374,231	129,294	175,132	$27,082
KCAG	2022	132,254	30,962	9,878	21,413	41,021	12,388	16,592	$24,007
KCAG	2046	151,090	35,428	11,484	24,076	46,903	14,076	19,123	$24,189
KCOG	2022	888,061	210,190	69,013	124,899	275,247	96,537	112,175	$27,435
KCOG	2046	991,974	233,539	74,192	138,638	311,939	106,427	127,239	$31,016
MCAG	2022	294,237	71,268	26,545	42,353	90,041	29,639	34,391	$27,844
MCAG	2046	337,828	82,038	30,391	48,361	103,415	34,005	39,618	$31,568
MCTC	2022	154,725	33,462	10,816	18,384	47,358	17,880	26,825	$29,135
MCTC	2046	198,171	42,950	13,388	22,573	61,178	22,847	35,235	$29,378
SJCOG	2022	792,490	166,934	58,653	105,114	252,361	93,424	116,004	$36,851
SJCOG	2046	944,756	205,524	67,348	122,018	305,838	109,716	134,312	$37,751
StanCOG	2022	562,224	120,860	41,014	74,650	179,523	65,024	81,153	$33,536
StanCOG	2046	674,401	145,111	49,121	89,457	215,581	77,835	97,296	$34,320
TCAG	2022	485,852	115,296	38,339	66,119	148,847	52,646	64,605	$25,512
TCAG	2046	563,835	134,380	43,907	77,529	173,893	59,453	74,673	$26,612

TABLE 70: POPULATION SIM WORKER INPUTS

MAREA	YEAR	WORKERS	15-19	20-29	30-54	55-64	65+	AVGPINC
FCOG	2022	379,183	9,194	80,313	216,828	56,159	16,689	$55,864
FCOG	2046	436,522	10,800	93,923	247,411	64,708	19,680	$55,263
KCAG	2022	51,133	1,227	13,807	27,360	6,561	2,178	$48,653
KCAG	2046	58,640	1,475	15,748	31,397	7,495	2,525	$48,828
KCOG	2022	338,057	8,788	80,086	188,728	46,759	13,696	$56,076
KCOG	2046	407,575	14,093	93,469	228,032	56,303	15,678	$59,355
MCAG	2022	105,758	4,011	24,482	60,036	13,209	4,020	$57,395
MCAG	2046	134,419	4,720	32,141	75,108	17,396	5,054	$60,302
MCTC	2022	58,883	1,489	11,696	32,936	9,019	3,743	$52,916
MCTC	2046	75,908	1,910	14,376	42,845	11,548	5,229	$53,112
SJCOG	2022	320,445	10,616	67,407	181,027	48,940	12,455	466,886
SJCOG	2046	396,041	12,612	81,591	226,266	60,610	14,962	$67,342
StanCOG	2022	225,835	7,338	49,283	127,222	34,932	7,060	461,751

StanCOG	2046	276,387	9,548	60,069	154,758	43,007	9,005	$62,166
TCAG	2022	193,194	6,094	41,803	106,914	29,083	9,300	$49,998
TCAG	2046	239,321	9,384	51,537	131,583	34,955	11,862	$49,957

TABLE 71: POPULATION SIM HOUSEHOLD INPUTS

MAREA	YEAR	HOUSEHOLDS	PERSONS	AVEHHSIZE	WORKERSPERHH	AVEHHINCOME
FCOG	2022	327,574	1,046,950	3.20	1.16	$87,210
FCOG	2046	373,725	1,189,709	3.18	1.17	$86,792
KCAG	2022	43,565	130,815	3.00	1.17	$72,881
KCAG	2046	50,047	149,651	2.99	1.17	$73,025
KCOG	2022	282,010	883,576	3.13	1.20	$86,393
KCOG	2046	347,716	987,489	2.84	1.17	$88,483
MCAG	2022	87,524	291,375	3.33	1.21	$93,607
MCAG	2046	114,027	334,966	2.94	1.18	$93,526
MCTC	2022	49,237	154,086	3.13	1.20	$91,556
MCTC	2046	63,265	197,532	3.12	1.20	$92,025
SJCOG	2022	248,394	784,339	3.16	1.29	$117,571
SJCOG	2046	304,962	936,605	3.07	1.30	$116,950
StanCOG	2022	182,417	558,252	3.06	1.24	$103,360
StanCOG	2046	224,144	670,429	2.99	1.23	$103,262
TCAG	2022	157,188	483,376	3.08	1.23	$78,855
TCAG	2046	195,387	561,359	2.87	1.22	$76,796

TABLE 72: POPULATION SIM HOUSEHOLD INCOME DISTRIBUTION

MAREA	YEAR	HOUSEHOLDS	<$25K	$25K-$50K	$50K-$75K	$75K-$100K	$>100K
FCOG	2022	327,574	34,514	79,126	48,530	92,766	72,638
FCOG	2046	373,725	39,757	89,779	56,511	104,163	83,515
KCAG	2022	43,565	8,112	10,691	7,218	9,369	8,175
KCAG	2046	50,047	9,300	12,270	8,308	10,778	9,391
KCOG	2022	282,010	43,818	59,972	53,654	46,405	78,161
KCOG	2046	347,716	50,897	72,377	65,398	56,937	102,107
MCAG	2022	87,524	9,947	16,545	15,805	16,815	28,412
MCAG	2046	114,027	12,699	22,218	20,555	21,717	36,838
MCTC	2022	49,237	561	10,461	9,863	18,033	10,319
MCTC	2046	63,265	820	13,174	12,553	23,442	13,276
SJCOG	2022	248,394	-	9,296	40,381	111,515	87,202

SJCOG	2046	304,962	674	10,883	49,222	137,062	107,121
StanCOG	2022	182,417	-	27,528	33,987	66,545	54,357
StanCOG	2046	224,144	-	33,823	41,771	81,762	66,788
TCAG	2022	157,188	26,143	29,463	26,039	44,581	30,962
TCAG	2046	195,387	35,953	36,309	31,232	54,674	37,219

TABLE 73: POPULATION SIM GROUP QUARTERS INPUTS

MAREA	YEAR	GQ	GQPERSONS	AVEGQINCOME	<$25K	$25K-$50K	$50K-$75K	$75K-$100K	$>100K
FCOG	2022	7,006	7,006	$15,514	6,065	594	174	32	141
FCOG	2046	7,986	7,986	$14,281	6,985	671	161	33	136
KCAG	2022	1,439	1,439	$30,404	263	1,094	59	22	1
KCAG	2046	1,439	1,439	$30,168	298	1,065	52	21	3
KCOG	2022	4,485	4,485	$11,046	3,999	361	99	18	8
KCOG	2046	4,485	4,485	$10,676	3,999	378	89	14	5
MCAG	2022	2,862	2,862	$16,942	2,476	230	75	3	78
MCAG	2046	2,862	2,862	$16,300	2,474	250	67	4	67
MCTC	2022	639	639	$12,056	519	120	-	-	-
MCTC	2046	639	639	$12,274	523	116	-	-	-
SJCOG	2022	8,151	8,151	$12,492	6,877	1,062	165	8	39
SJCOG	2046	8,151	8,151	$12,624	6,860	1,077	161	11	42
StanCOG	2022	3,972	3,972	$11,284	3,505	392	62	6	7
StanCOG	2046	3,972	3,972	$11,334	3,516	375	73	4	4
TCAG	2022	2,476	2,476	$12,338	2,177	273	13	6	7
TCAG	2046	2,476	2,476	$11,858	2,199	258	7	1	11