The Freight Landscape: Using Secondary Data Sources to Describe Metropolitan Freight Flows

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Abstract

Metropolitan areas around the world are seeking to better manage freight flows and reduce negative impacts on local populations. A major challenge to better urban freight management is the lack of data; little is known about freight movements at the intra-metropolitan level. We develop the concept of a freight landscape: spatial patterns of freight activity. We use population and employment density quartiles to explain spatial patterns of development in four metropolitan areas in California: Los Angeles, San Francisco, Sacramento and San Diego. We hypothesize that the freight landscape can be described using data on population, employment and transport system supply. We test the concept using network model data for the Los Angeles region and San Francisco region. We find that in both cases, our simple proxies have significant explanatory value, and hence may provide an effective means for approximating spatial patterns of freight activity.

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1 INTRODUCTION

Countries and cities around the world are connected by economic interactions that generate flows of people, goods, information and money. Large gateway cities function as logistics hubs in the global freight network, while the concentration of population and production in these cities also generate substantial demand for goods movement. The volume of freight moving within and across metropolitan areas is increasing due to more complex supply chains, changing consumer and business preferences, and the rise of e-commerce (Dablanc and Rodrigue, 2014). Freight movements are a problem in cities around the world. Though essential for the functioning of metropolitan areas, freight generates negative externalities such as air pollution, noise, and GHG emissions, and contributes to congestion (Giuliano et al, 2013).

Efforts to better manage freight are constrained by lack of data and methodological tools. Basic data such as the number of trucks operating in a metropolitan area, number of deliveries taking place in commercial districts, or of truck volumes on major streets is virtually unknown and typically not available except via costly one-time surveys. Urban freight modeling research has developed various types of freight trip generation methods, but freight generation does not provide a sufficient portrayal of the overall impacts of freight across various locations. There is little research on the relationship between spatial structure and freight flows, in contrast to the extensive literature on spatial structure and passenger flows. A better understanding of these relationships would improve our ability to understand the dynamics of urban freight distribution and to design more effective solutions to urban freight problems.

This research explores the relationship between population distribution, employment distribution, transport system supply, and freight flows in California's four largest metropolitan areas. We present the concept of "freight landscape" – a description of freight activity imputed from population, employment and transport network characteristics. In the absence of detailed, fine grain data, the use of secondary data provides a framework to approximate freight supply, demand, and flow; to take advantage of existing but sparse freight flow data; and to conduct more strategic data collection to generate more precise freight flow estimations.

1.1. Freight in Metropolitan Areas

Metropolitan freight activity may be described as of two main types: freight related to local supply or demand, and freight related to national or international trade. Globalization has increased as a result of transport and communications technology as well as trade liberalization policies (Dicken, 2007). Production supply chains have become more complex as producers seek out comparative advantage opportunities around the world. Goods production processes – spatially fragmented but temporally integrated -- connect countries and cities into 'global production networks' demanding cost-efficient and timely flow of goods (Capineri and Leinbach, 2007). The outcome is consistent growth in cross-border trade for the last several decades. In the US, total foreign merchandise trade increased by nearly one third from 2000 to 2012 (FHWA 2014).

1.1.1 Global and local flows

Large metropolitan areas are the major nodes of the global production network, containing the largest ports, airports and intermodal facilities. For example, the top 25 import/export facilities in the US are located in 15 metro areas; they accounted for 44% of total trade of $3.7 trillion in 2011. The top 5 (Los Angeles, New York, Detroit, Houston, and Laredo) account for 27% of the total (FHWA, 2014).These metro areas serve as transshipment nodes, consolidating exports or distributing imports, as well as major centers of production and consumption. Rodrigue (2004) notes that these gateway cities are usually located in 'mega-urban regions' through which logistics functions are geographically and functionally integrated at the local, regional, and global levels. These regions developed historically as points of trade. With large and concentrated population and economic activity, they generate much of the trade demand and provide the array of expertise for managing global supply chains. Large US metropolitan areas – those with population of 1 million or more – account for over 90% of freight shipment origins and destinations by value. The concentration of trade in large metro areas means concentrated demand on the rail and highway systems. Eleven of the top 25 highway bottlenecks are located in Los Angeles and Chicago (Cambridge Systematics, 2005). In a ranking of corridors (highway segments) by Inrix for 2014, Los Angeles and New York have 13 of the worst 25 corridors.

The second type of freight activity is associated with the supply and demand of the local population: the "last mile" delivery or pickup of imports/exports, and the intra-metropolitan trade of commodities (local production and consumption). Freight related to local supply and demand is also increasing due to longer and more complex supply chains, increasing velocity within supply chains (e.g. just-in-time practices), the rise of e-commerce, and overall per capita income, population and employment growth. Increased freight activity at the metropolitan level means increased truck trips and vehicle miles traveled. Unfortunately, there is no data source for metropolitan truck traffic in California or the US. European data suggests that truck traffic accounts for 10-15 percent of total urban vehicle traffic (BESTUFS, 2006).

Our research is aimed at understanding both types of freight activity. The Los Angeles and San Francisco metropolitan areas are major international import/export nodes. San Diego has concentrated cross-border trade, while Sacramento functions as a regional market. Together these metropolitan areas provide a variety of contexts for examining freight flows and urban form.

1.2 Organization of Report

The scope of our research changed as a result of data limitations. We were going to conduct case studies of Los Angeles, San Francisco, and San Diego, and estimate models of freight activity as a function of local and regional spatial characteristics to test the freight landscape concept. Model estimation requires network flow data for trucks, which we obtain from regional transportation planning simulation models. San Diego did not have separate truck flow data, and consequently models could not be included in the formal tests. To compensate for the loss of the San Diego statistical analysis, we added Sacramento as a fourth case study to include in the descriptive portion of the analysis.

We construct the freight landscape models by estimating the intensity of truck activity as a function of land use characteristics. We expect flow density to be related both to transport system supply and demand, all else equal. As a means to evaluate our results, we also estimate models of the intensity of all vehicle activity. We estimate models in two forms. In the first we use categorical measures of population and employment development density, and in the second we use measures of population and employment characteristics. We control for spatial correlation and access to major facilities.

The remainder of this report is organized as follows. Chapter 2 presents a literature review on freight flows and urban form. Chapter 3 introduces the freight landscape concept, and presents a descriptive analysis of the four case study metropolitan areas. Chapter 4 presents data, method and results of our formal tests for Los Angeles and San Francisco. Chapter 5 presents a summary of the research, some observations on the freight landscape concept, and a discussion of policy implications.

2 LITERATURE REVIEW: FREIGHT AND URBAN FORM

This chapter is an evaluation of current documentation on the relationship between freight activity and urban form. While urban form affects the type of volume of freight activity that a city can accommodate, there have been relatively few studies that describe the mechanisms through which freight activity and urban form shape each other.

2.1 Overview

Most cities prior to the auto age were built around freight facilities due to the high cost of moving goods on land. The earliest cities developed around ocean or river ports. Later, cities developed around railroad terminals, with manufacturing clustering around these major transport nodes. With the advent of the truck, freight could move ubiquitously at relatively low costs, reducing the need for industry to locate near major water or rail nodes and hence contributing to the decentralization of population and employment witnessed throughout the 20th century. The shift to a service and then information economy also played a role in this process.

2.1.1 Freight transport infrastructure location

Metropolitan freight flows are the result of the spatial distribution of freight supply and demand, and the transport supply. In general, freight transport supply is fixed. The major transport nodes – ports, airports, rail terminals – are mostly an historic legacy from the 19th and 20th centuries. Because of their size and value they remain fixed in place, despite population growth and changes in economic structure.

When examining road freight transport, in sharp contrast with other freight modes, urban form is determined first and foremost by the provision of transportation infrastructure for personal transport. As noted by Boarnet and Crane (2001), urban travel patterns are affected by supply as well as demand. Cities that have ample provision of highway infrastructure and lack natural barriers to growth will tend to have a more dispersed urban form when compared to cities that are constrained by natural barriers and/or choose to invest more heavily in mass transit. In most cases, trucks piggy-back on infrastructure that was designed to accommodate passenger travel demand. For this reason, a city that is generally ill suited to efficiently handle auto traffic will generally also inhibit freight activity. As stated by Cherrett,

> *This is not to say, however, that freight journeys are unaffected by urban form. Clearly, factors such as settlement size, density, and commercial and industrial land use patterns are likely to influence the extent and location of urban freight activity as well as the operating patterns and types of vehicles used for freight work that takes place to and within the urban area (Allen, Brown and Cherrett, 2012 p. 46)*

2.1.2 Freight and land use

The location of freight supply and demand is determined by the location choices of businesses and households. In general, freight intensive activities (manufacturing, warehousing and distribution) make location choices by trading off land and transport costs. These activities tend to be large scale and land intensive, making land price a critical factor.

Cities, through their zoning authority, can affect the overall supply of industrial land and its location, also affecting land prices. As cities have de-industrialized and the value of land close to the city center has increased, there is a growing intolerance for freight activity due to its impacts on noise, vibration, emissions, safety and congestion as well as visual blight. For this reason, cities have increasingly relied on zoning changes to restrict the use of freight, even in areas originally designated for freight activity (Meitzen et al, 2012). Freight locations, and consequently freight trips are increasingly determined not by economic optimization but by locating in those areas in which their presence is still permissible and where this permission is unlikely to be revoked. Through concentration, freight users can cluster their impacts and thereby reduce the total area impacted by the various negative externalities (Boile and Theofanis, 2009).

The encroachment of incompatible land use on freight activity has different impacts for different modes. For water transportation, the transition of industrial waterfronts for residential and tourism use is a major challenge. For rail corridors, the development of land that borders rail corridors is problematic. For rail terminals, which are often located near the central business district, the increased value of the land threatens to dislodge these terminals and thereby disrupt the rail network. Several areas have examined potential rail relocation as a mechanism for alleviating this issue, yet it remains prohibitively costly in most instances (Meitzen et al, 2012).

There is little research on how freight dynamics may influence or be associated with land use patterns at the intra-metropolitan scale. It is generally observed that urban freight is inefficient due to 1) restrictions on routes and delivery time windows; 2) parking and loading limitations, 3) a larger share of small deliveries (including home deliveries), and 4) inventory and replenishment practices of urban retailers (Holguin-Veras, et al, 2005; Giuliano et al, 2013; Xing et al, 2010; Bomar, Becker and Stollof, 2009).

There is evidence that freight activity and congestion is associated with density. Studies of New York City show very high rates of deliveries to restaurants in Manhattan (Holguin-Veras et al., 2005), as well as higher rates of illegal truck parking in Manhattan than other parts of the city (Bomar, Becker and Stollof, 2009). In addition, most urban freight mitigation programs focus on the city core (Giuliano et al, 2013).

2.1.3 Empirical studies of warehousing and distribution

There is a growing literature on warehouse and distribution facility location. These studies document land price and availability as the dominant factor. Klastorin finds that in general, firms tend to prioritize land costs over transportation costs, particularly in cases where they do not derive direct benefits from servicing the surrounding area (Klastorin et al, 1995). The implication for distribution centers is that, all else equal, they will tend to locate in the periphery of cities rather than in areas that are closer to their customer base but result in higher land costs. A recent study of warehousing and consolidation in Great Britain observes that British companies have been increasingly consolidating warehousing locations in order to have better hinterland access (Allen, Browne and Cherret, 2012). "Although freight transport costs may increase as a result of these location decisions, these cost increases are more than offset by the cost savings resulting from the centralisation of stock" (Allen, Browne and Cherrett, 2012 p. 3). For Paris, Dablanc and Rakotonarivo (2010) note that parcel transport terminals have consistently moved outward from the city center since the 1970s. This study also gauges the impacts in terms of additional CO_2 emissions that result from these more distant locations relative to the city center examined changes in the location distribution on logistics services in the Tokyo metro area (Sakai et al, 2015). They find consistent decentralization, despite very high transport costs. As logistics facilities consolidate into fewer larger facilities located further from the city center, they generate additional VMT and the various associated negative externalities (Sakai et al, 2015).

In California, studies of warehouse and distribution center location have been conducted for the Los Angeles metro area by Dablanc, et al. (2014). Dablanc and co-authors measured the average distance of each W/DCs to the geographic centroid (barycenter) of all W/DCs in 1998-2009. The average distance of W/DCs to the barycenter of the urban area increased by 23% (from 25.9 to 32.0 miles). A current study commissioned by the Southern California Association of Governments (SCAG) is nearing completion. It examined not only where warehouses were located but also their other attributes. The study found that vacancy rates throughout of region were extremely low. Warehousing has been pushed to the periphery of the region not due to a preference for distant warehousing space, but to the infeasibility of accommodating demand within the more developed parts of the region. (Cambridge Systematics, 2015).

2.2 Modeling approaches for generating freight flows

The spatial pattern of freight supply and demand ultimately determines the freight flows observed on the transportation system. Freight models that predict freight flows from a given distribution of freight supply and demand are a growing topic of research. There are multiple methods. The choice of method depends on the degree of available data, the need to model various interaction effects, the need to account for technological change over time, and the need to tie in freight activity with broader forces in the economy. (Kuzmyak 2008 p. 10)

Urban freight demand modeling is more difficult than passenger demand modeling for two reasons. First, there are no equivalent resources to the basic data gathered for passenger travel – population characteristics, journey to work data, or travel survey data. As noted in Chapter 1, there is no readily available, consistently collected data source for sub-metropolitan freight movements or characteristics. Second, freight patterns are highly sensitive to economic conditions and prices. Thus, even if the data were available, predicting freight flows would be more uncertain than predicting passenger flows. In addition, until recently (past few decades), there has been little interest in incorporating freight into metropolitan travel demand models. In most metro areas freight constitutes a small portion of total traffic, and using approximate methods such as factoring are “good enough.” For these reasons, freight models are less well developed and produce less reliable results than passenger models (Novak et al, 2011).

2.2.1 The Four Step Approach

Some models have been adapted from the traditional four-step passenger traffic-demand model. This approach fails to take into account some of the specific attributes of freight and hence can lead to false or incomplete conclusions. The behavior of freight operators is quite distinct from that of general traffic. In some ways, the activities of freight providers are more economically rational than general traffic. For example, freight operators seek to minimize transportation costs and will often alter behavior rapidly in response to small shifts in macroeconomic conditions.

As described by the FHWA, freight modelling involves the transforming of economic factors into freight generation rates. The most typical employment estimates used for freight generation include North American Industry Classification System (NAICS) or Harmonized System (HS) codes. One weakness of using these data sources is that specific employment totals are often suppressed for confidentiality reasons, particularly at higher levels of disaggregation (Novak et al, 2011).

Rather than tying the outputs to the specific economic characteristics of residents within each Transportation Analysis Zone (TAZ), in four-step freight modelling inputs are measured in terms of either commodities or vehicles. Outputs are always measured in terms of vehicles. Trip generation rates are based on specific multipliers by industry and by truck type (FHWA, 2013). Truck trip generation "is determined by regressing the number of commercial vehicles on the number of employees in various industries and household population" (Yoon and Kim, 2009, pp. 4). In multiple regression, "Trip generation rates represent number of trips started and ended by trucks per unit of explanatory variable" (Kulpa, 2014 p. 199). The difficulty in producing accurate models of freight generation by this manner is clear from the fact that the generation of freight trips is a multistep process. Therefore, it is difficult to assign freight generation to a specific geography in a way that is analogous to passenger transportation. In other words, at what point in the supply chain can we reliably say that the freight trip was generated? Another complicating factor in four step modelling for trucks is the different trucks have different impacts on the roadway network. The breakdown of trucks by type can also be difficult to project absent direct observation, which can dramatically drive up data collection costs (Kuzmyak, 2008).

Four-step models for trucks can be paired with other freight generation models to describe the impacts of other modes. For rail, the most commonly used tool to generate rail trips is the Carload Waybill Sample, generated by the Surface Transportation Board (FHWA, 2013). Modelling rail flows is even more challenging as the rail system is fully controlled by a few private operators and, for this reason, it is exceedingly difficult to model freight rail activity based on input-output models - particularly at a small geographic scale. For this reason, future estimates of rail activity are sometimes simply extrapolated from past trends as opposed to generation through formal modelling. Similarly, while national or international level maritime freight forecasts are modelled based on economic multipliers, more frequently forecasts are based on individual ports or terminals.

2.2.2 Commodity based models

Another approach to freight modeling is to directly model the economic exchange of goods, and from these commodity flows derive the transport or shipping flows. Commodity based models, of which the Freight Analysis Framework (FAF) is the most well-known, rely on input-output models of economic activity. The FAF is designed to simulate interstate flows, and thus has limited utility for sub-metropolitan modeling. The FAF is sometimes used to generate control totals for flows in and out of the metro area by commodity type and mode.

The commodity based approach requires a method for translating the economic flow (dollar value of a given commodity) to a tonnage flow, and then to a truck flow. Typically, average values by sector are used for the value to weight conversion. The conversion from weight to truck trips tries to take into account empty return trips, etc. This process is subject to many errors. Thus, although the commodity approach is behaviorally more robust, it may or may not generate better results than the four-step model.

Another alternative is a Supply Chain/Logistics model, which models life cycles of products and their transportation considerations. One weakness of these models, as described by NCFRP, is that they tend to overstate the ability of freight to shift between modes. (Cambridge Systematics, 2010) For both supply chain and input output based models, the efficacy of their projections tends to diminish at smaller geographic scales. (Cambridge Systematics, 2010)

2.3 Real Time Freight Tracking

Due to the weaknesses in traditional freight models described above, researchers have sought methods to directly measure freight activity, particularly for truck movements in urban areas and within other environments such as marine and rail terminals. One of the most promising sources of data on urban freight flows are trucks equipped with GPS which allows their daily activity to be tracked. (Cambridge Systematics 2010) One area of precision that is better explained through GPS trackers is freight trip chaining, which is particularly essential when explaining less- than truckload (LTL) and small parcel delivery truck behavior. As stated in NCFRP Report 8, "Chaining of freight activities could be addressed by use of GPS data." (Cambridge Systematics, 2010, p. 13) The processing of historical GPS data that no longer has commercial strategic importance is a particularly attractive data source.

Fleet managers are increasingly installing GPS on their trucks as an internal business decision in order to prevent inefficient practices. In some cases, historical records may be made available to researchers. In addition to trucks, GPS trackers as well as active RFID transponders are also commonly installed on individual containers and pallets, allowing for an even higher level of transparency on how freight moves through the supply chain. Active RFID tags emit their own signal and for this reason have a much longer read range. The instillation of active RFID on all equipment, including empty containers and chassis helps logistics firms to identify stages in the supply chain that are less productive and can enable firms to test the efficacy of new procedures (Lieberthal, 2011). As is the case with GPS records for trucks, archived RFID records can serve as a potentially powerful new data source.

Recently, terminals have started to rely on Bluetooth scanners in order to track precise movements of vehicles as they move throughout a terminal or industrial park. As each Bluetooth device emits a unique signal, scanners are able to track individual vehicles through each stage of the delivery process by reading the signal from the driver's mobile device. As not every driver carries a Bluetooth enabled mobile device, and not every driver will have his/her device enabled while servicing a terminal, this technique cannot be used to perform traffic counts, however it can be used to model probe vehicles.

2.4 Summary

This chapter has presented an overview of the relationship between transport system supply, land use and freight activity location. We observe that land prices and zoning constraints heavily influence the location of freight intensive activities such as warehousing and distribution and explain observed decentralization trends. We note that major nodes are spatially fixed, and the system adapts to changing spatial patterns of supply and demand by trading off increased transport costs (and hence increased freight flow on the network) for lower land costs.

The lack of zone or tract scale data on truck movements, deliveries, or shipping patterns leaves modeling as the primary tool for estimating sub-metropolitan freight flows. The two most widely used approaches are variants of the four-step passenger demand model, and commodity based methods that rely on economic input/output data. Both models implicitly assume a relationship between land use and freight flows. For example, land use is the input for freight generation and attraction in the four-step model. Both approaches require highly detailed sector level data, any many assumptions about how the underlying demand is expressed as truck trips on a network.

The last part of the chapter provides a brief review of methods for obtaining more data on freight flows and truck travel patterns.

3 THE FREIGHT LANDSCAPE AND FOUR CASE STUDIES

As summarized in the previous section prior research has shown that urban spatial structure influences freight flows, but little is known about systematic relationships. We hypothesize that freight flows generated by economic activities depend systematically on the spatial organization of freight suppliers and demanders, as well as on the transportation facilities within the metropolitan areas.

3.1 Conceptual framework

There are many different types of freight flows in metropolitan areas. For example, Dablanc and Rodrigue (2014) describe the distinctions between consumer and producer flows. Consumer flows include independent and chain retailing, food deliveries, and parcel and home deliveries. Producer flows include industrial production, warehousing and distribution, construction materials, and waste. Each is associated with a unique supply chain, and hence unique flow characteristics. We use the example of retailing to illustrate, and consider how development density – the combined effects of population and employment density – might affect retail deliveries. We illustrate in Figure 3.1.

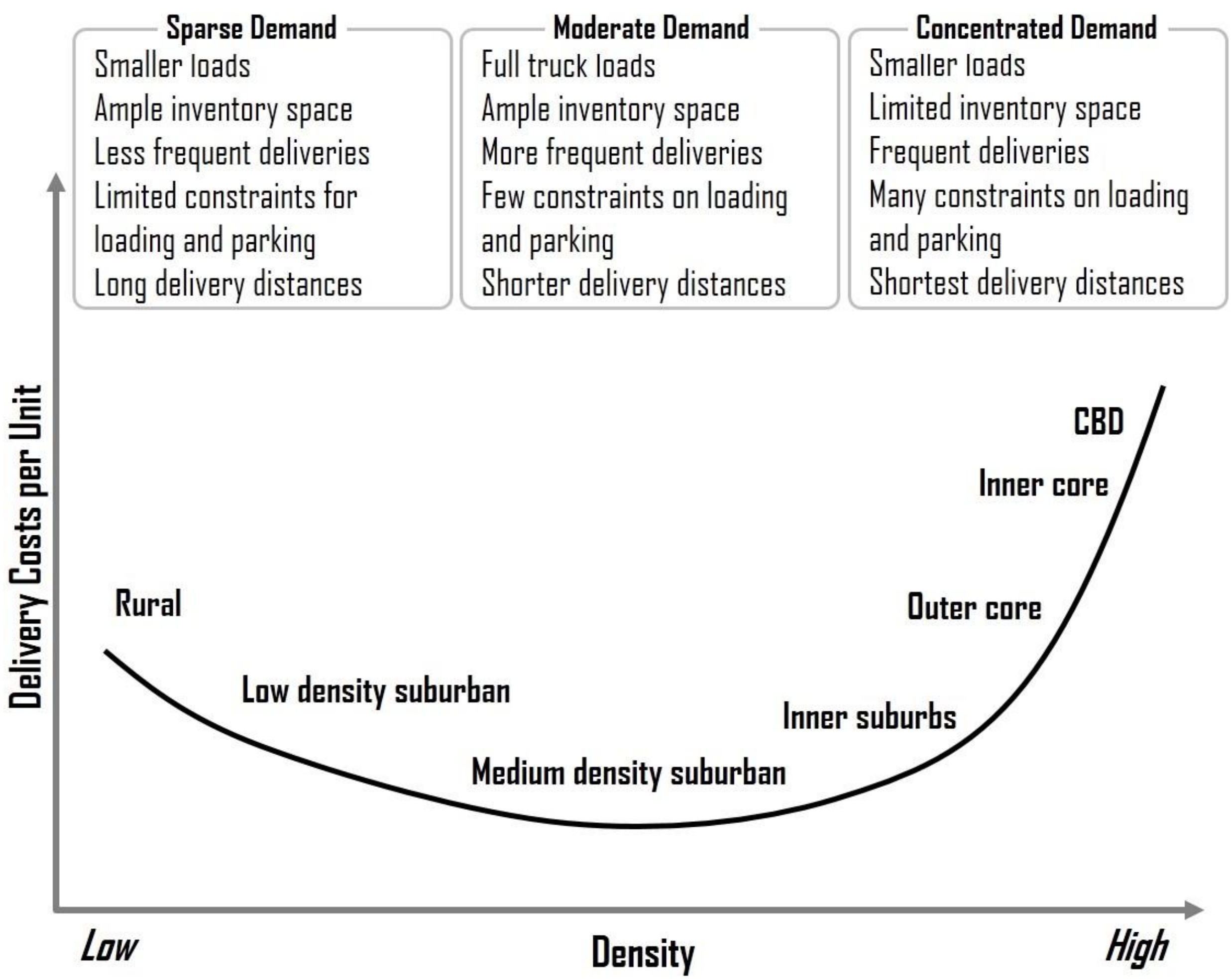


Figure 3. 1 Development density and delivery costs for retailing activities

In rural areas with dispersed population and economic activity, delivery costs are relatively high due to smaller loads and long delivery distances, even though road capacity is not a constraint. In suburban areas, there is still adequate transport supply, and the greater density of demand makes deliveries more efficient. Trips are generally shorter due to proximity to warehouse/distribution centers. When we approach higher levels of urban density, delivery costs increase at an increasing rate. Higher density is associated with higher land values, and higher land values lead to more intense use of the space available. For retailers, this necessitates more revenue per square foot, more rapid turnover of product, and less space devoted to storage, compared to retail activities in lower density environments. A similar dynamic is at work for commercial businesses and residences.

Higher population density is also associated with higher diversity in product types more product and consumption diversity, especially in areas with higher income populations. This diversity is exhibited by greater prevalence of independent retailers (restaurants, specialty clothing, etc.) who together offer a broad spectrum of consumer goods and services and hence use a wide variety of suppliers for relatively small volume orders. These relationships imply more and smaller shipments. Finally, higher density implies more frequent basic services (trash pickup, maintenance services, etc.). These more frequent truck activities take place in an environment of limited parking and loading facilities and intense competition for scarce road, curb and sidewalk space (Dablanc et al, 2013). At the highest density, truck size may be limited, again increasing trip frequency and cost. We therefore expect the attributes of freight flows (frequency, volume, vehicle mix, etc.) to vary with development density.

Development density, transport demand, and transport infrastructure capacity are interdependent. The high price of land promotes more intense utilization (and hence transport demand), while also making the provision of transport capacity ever more costly. Thus we observe congested roads, rail networks, and sidewalks in the densest parts of cities.

The freight landscape is based on development density: the combined density of both population and employment. Freight demand is generated by both households and firms. We argue that the overall intensity of land use, which reflects underlying land prices, is the critical factor in explaining the volume and characteristics of freight flows. However, development density occurs in different combinations. Some areas may have high population density, but low employment density (multi-family residential neighborhoods) others may have the reverse (manufacturing zones). We expect that freight flows will differ accordingly. Truck traffic should be relatively low in the first case and relatively high in the second, even though the development density may be the same. Thus our freight landscape measure should take into account the relative proportions of population and employment, as well as the combined density. To operationalize the concept, we use combinations of population and employment density. We combine quartiles of both to generate a 16-category freight landscape measure.

3.2 Case Study Areas

We use California's four largest metropolitan areas to test the freight landscape concept. For all four metro areas, we generate the development density measure, map the landscape, overlay the transport network, and describe similarities and differences. For Los Angeles and San Francisco, we conduct formal tests of the relationship between development density and freight flows. This chapter presents the data and descriptive analysis; model results are presented in Chapter 4.

The Los Angeles, San Francisco, San Diego and Sacramento metropolitan areas are quite diverse and thus provide good cases for testing the concept. Table 3.1 gives population, employment, and area size using 2010 data. Los Angeles, the second largest CSA in the US, has roughly twice the population and employment as San Francisco, and four times more area. San Diego and Sacramento are much smaller in population and employment, but more comparable to San Francisco in area. Because CSAs are built from counties, each metro area has a substantial portion of land that has little or no population. We eliminate these undeveloped areas from our analysis (see Section 3.2.2)

Table 3. 1 Population, Employment, Area Size, 2010

	Population	Employment	Size (Sq-KM)*
Los Angeles CSA	17,872,394	7,034,637	88,049
San Francisco CSA	7,133,524	3,142,824	18,246
San Diego MSA	3,095,313	1,230,279	10,895
Sacramento CSA	2,414,783	908,342	18,871

* We use metric units, because this project is part of a larger international research program with all partners using metric system.

The metropolitan areas differ in other ways. Los Angeles is the nation's number one international trade node. San Francisco is also a major international trade center, but in higher value goods. San Francisco is the most geographically constrained, with the bay in the middle and with parts of the area surrounded by steep hills. Sacramento is a trade node for the central valley, and San Diego serves as a hub for cross-border trade and industry. The four metro areas also differ in transport supply. San Francisco and San Diego have relatively extensive highway systems relative to population. According to FHWA (Federal Highway Administration), in California, San Diego has the largest ratio of freeway lane-miles per 1,000 population in 2008: 0.65, followed by San Francisco (0.57), Los Angeles (0.47), and Sacramento (0.43). Los Angeles has the nation's largest ports and five major airports. These differences should lead to different development density patterns and freight flows.

3.2.1 Data sources

This section describes all of our data and data sources.

3.2.1.1 Metropolitan Areas

We define metropolitan areas as a contiguous set of cities or counties that are economically integrated. Economic integration means significant exchanges of people (commuting) or goods (shipping) across borders. The closest census definition is the CSA (Combined Statistical Area) for multi-county metro areas, and MSA (Metropolitan Statistical Area) for single county metro areas. Our case study areas are:

- Los Angeles-Long Beach-Riverside, CA CSA (**Los Angeles CSA**) consists of three MSAs, 5 counties in total: Los Angeles-Long Beach-Santa Ana, CA MSA (Los Angeles and Orange County); Oxnard-Thousand Oaks-Ventura, CA MSA (Ventura County); and Riverside-San Bernardino-Ontario, CA MSA (Riverside and San Bernardino County).

- San Jose-San Francisco-Oakland, CA CSA (**San Francisco CSA**) consists of six MSAs, 11 counties in total: Napa, CA MSA (Napa County); San Francisco-Oakland-Fremont, CA MSA

(Alameda, Contra Costa, Marin, San Francisco, and San Mateo County); San Jose-Sunnyvale-Santa Clara, CA MSA (San Benito and Santa Clara County); Santa Cruz-Watsonville, CA MSA (Santa Cruz County); Santa Rosa-Petaluma, CA MSA (Sonoma County); and Vallejo-Fairfield, CA MSA (Solano County).

- Sacramento-Arden-Arcade-Yuba City, CA-NV CSA (**Sacramento CSA**) consists of four MSAs, 8 counties in total: Gardnerville Ranchos, NV miSA (Douglas County, excluded); Sacramento-Arden-Arcade-Roseville, CA MSA (El Dorado, Placer, Sacramento, and Yolo County); Truckee-Grass Valley, CA miSA (Nevada County); and Yuba City, CA MSA (Sutter and Yuba County). We excluded Douglas County, NV from the study area. * miSA is Micropolitan Statistical Area.

- San Diego-Carlsbad-San Marcos, CA MSA (**San Diego MSA**) consists of one county in total: San Diego County.

We use the 2009 Census definition of the CSAs, the closest year to the 2010 target year of our data.

3.2.1.2 Population, Employment, and Transport System Data Sources

Population data are from the 2010 US Census. Employment data are from the 2010 Longitudinal Employer-Household Dynamics program (LEHD). LEHD is based on unemployment insurance wage data, the Quarterly Census of Employment in Wages, and the Office of Personnel Management data. Two-digit North American Industry Classification System (NAICS) industry sector employment counts are available at the census block level. We aggregate to census tracts. LEHD includes all employment, except military, the self-employed, and the informally employed.[1] For the Los Angeles and San Francisco CSAs, we use Transportation Analysis Zones (TAZs) as our geographic unit in order to better link our transportation network data. TAZs are approximately the same size as census tracts. Census tracts often have boundaries along major highways or arterials; TAZs are configured to include these facilities within boundaries. We use aerial apportioning to convert from census tracts to TAZs. The TAZ geography is provided by the Metropolitan Planning Organizations (MPOs), SCAG and the Metropolitan Transportation Commission (MTC). All data are in ArcGIS shapefiles.

Transportation and traffic data include highways, major arterials, collectors, freight railways (LA only), and major freight nodes – airports, seaports, and intermodal facilities. Road transportation system and traffic data are also provided by the MPOs. We obtained output from regional transportation plan (RTP) models: the 2008 SCAG RTP model for Los Angeles and the 2010 MTC/ABAG RTP model for San Francisco. RTP models generate link flows by time of day and vehicle type.

Seaport location data were retrieved from World Port Index. Seaport statistics are from USDOT Maritime Administration 2013 Vessel Calls data. We include following ports as major freight nodes: Port of Los Angeles, Port of Long Beach, Port Hueneme, San Francisco Bay Area (San Francisco, Oakland, Richmond, Redwood City), Port of San Diego, Port of Stockton, and Port of West Sacramento.

Cargo-service airport location data were retrieved from FAA (Federal Aviation Administration, ACAIS 2013 data). Cargo-service airport statistics are from Federal Aviation Administration 2014

[1] http://lehd.ces.census.gov/applications/help/onthemap.html#!faqs#7

Air Carrier Activity Information System data. We include cargo service airports that received more than 100 million lbs. landed-weight. Included are LAX (Los Angeles International), SFO (San Francisco International), SJC (Norman Y. Mineta San Jose International), ONT (Ontario International), OAK (Metropolitan Oakland International), LGB (Long Beach), SAN (San Diego International), MHR (Sacramento Mather), and SMF (Sacramento International).

Location data for intermodal facilities were retrieved from the Intermodal Association of North America (IANA). Freight rail and intermodal facility statistics are from Caltrans Freight Planning Fact Sheets. We include only rail-to-truck facilities, given our focus on truck traffic. Airport-to-truck facilities are geographic duplicates of airport location. Included facilities are BNSF San Bernardino, BNSF LA Hobart, BNSF Stockton, BNSF OIG, UP Los Angeles, UP LATC, UP City of Industry, UP ICTF, UP Oakland, and UP Lathrop.

3.2.2 Exclusion of sparsely populated areas

CSAs are constructed on the basis of counties, and therefore may include areas that are sparsely populated, such as national forest or other protected areas, deserts, or agricultural land. Our interest is in urban freight, so we exclude the least populated tracts or TAZs from each metro area. We define 'sparsely populated areas' as zones with population and employment density lower than the one-tailed 1.65 standard deviations from the mean of the natural log form of the variables. In the standard normal distribution, 5% of each sample falls in this category. Population and employment density measures are separately calculated, and we eliminate zones with both population and employment density below the given thresholds. We keep zones if either population or employment density is above the criterion. In this way, high-employment and low-population density zones or low-employment and high-population density zones are retained.

We present summary statistics before and after the low-density zone elimination below in Table 3.2. The share of census tracts/TAZs eliminated ranges from 4.3% in San Francisco to 7.6% in Sacramento. The share of population and employment eliminated ranges from about 1 to 6% and 2 to 4% respectively. In contrast, about 77% of the land area is eliminated. Los Angeles has the largest share eliminated (84%). Los Angeles and San Bernardino Counties include extensive national forest and uninhabited desert. Figures 3.2 a-d show the included and excluded areas for each metro area.

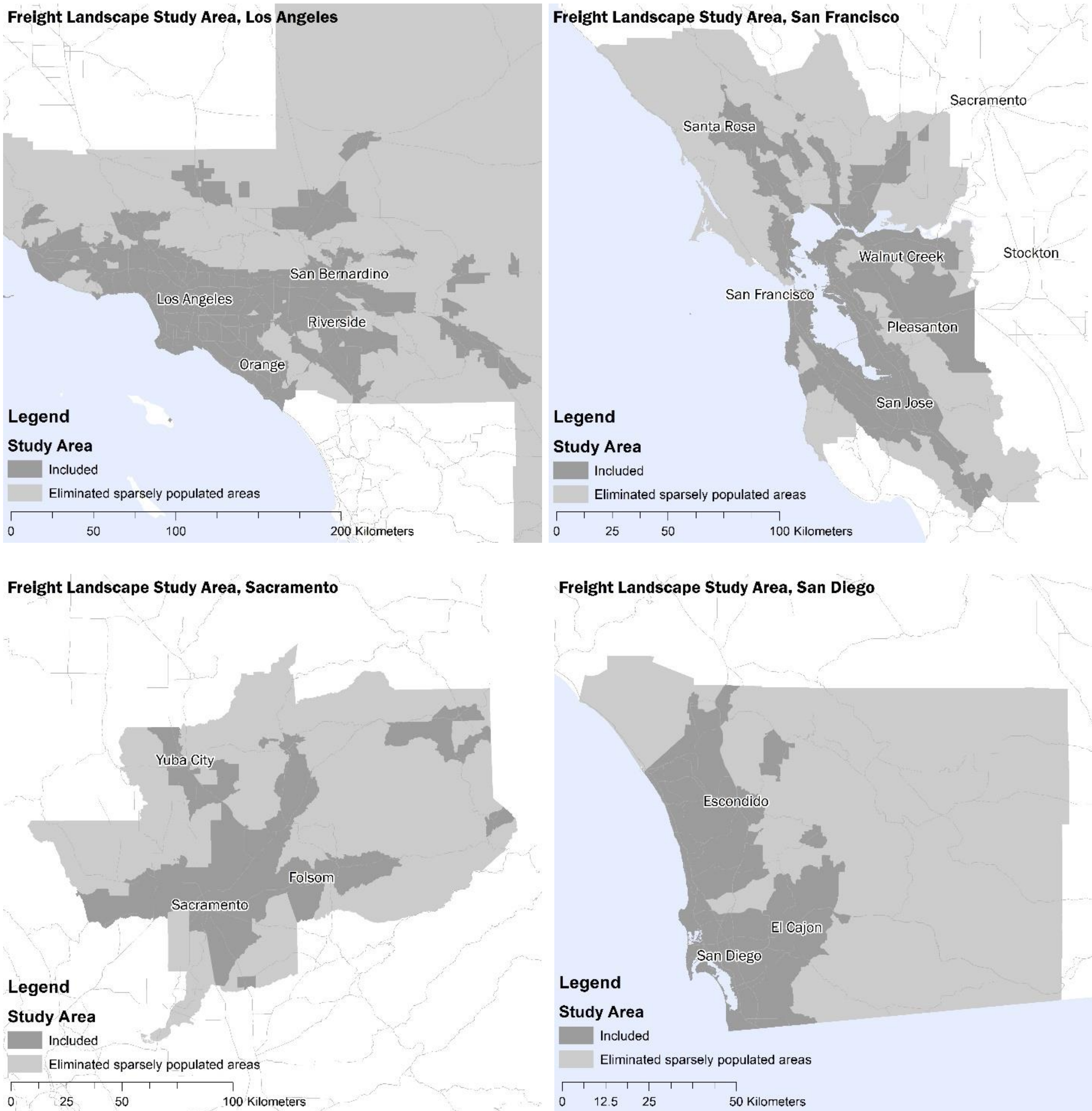


Figure 3. 2 a-d Included and excluded portions of metro areas

Table 3. 2 Sparsely developed area exclusions

Los Angeles

	Whole sample	Cut-off threshold (people/sqkm)	Study area	Difference	Eliminated Percentage
TAZ	3,999	-	3,789	210	5.3%
Population	17,872,394	52.05	17,634,468	237,926	1.3%
Employment	7,034,637	14.30	6,995,204	39,433	0.6%
Square kilometer	88,049	-	14,010	74,039	84.1%

San Francisco

	Whole Sample	Cut-off threshold (people/sqkm)	Study area	Difference	Eliminated Percentage
TAZ	1,454	-	1,398	56	3.9%
Population	7,133,524	204.37	6,840,367	293,157	4.1%
Employment	3,142,824	30.90	3,082,215	60,609	1.9%
Square kilometer	18,246	-	6,971	11,275	61.8%

Sacramento

	Whole sample	Cut-off threshold (people/sqkm)	Study area	Difference	Eliminated Percentage
Census Tracts	541	-	500	41	7.6%
Population	2,414,783	49.42	2,269,230	145,553	6.0%
Employment	908,342	5.91	882,384	25,958	2.9%
Square kilometer	18,871	-	5,444	13,427	71.2%

San Diego

	Whole sample	Cut-off threshold (people/sqkm)	Study area	Difference	Eliminated Percentage
Census Tracts	627	-	598	29	4.6%
Population	3,095,313	206.56	2,928,770	166,543	5.4%
Employment	1,230,279	21.17	1,207,606	22,673	1.8%
Square kilometer	10,895	-	2,471	8,424	77.3%

3.3 Population and employment distribution

In this section we discuss the population and employment distributions, generate our development density measure, and discuss patterns across the four case study areas.

3.3.1 Population and employment density descriptive statistics

Table 3.3 gives descriptive statistics for population and employment density. The mean population density is up to three times greater than that of employment density, because total population is always larger than total employment. San Francisco and Los Angeles have notably higher densities than Sacramento and San Diego, as expected. The employment distribution is more skewed than population. Peak employment density is markedly higher than peak population density, whereas average employment density is lower than that of population. The magnitude of the mean proportional to the median of employment is also substantially larger than that of the population in four metropolitan areas, which implies that a large share employment is concentrated in a few high-density zones.

The relative concentration of employment varies across metropolitan areas. The ratio of the peak to median employment density is the largest in Los Angeles CSA (440.8), followed by San Francisco CSA (229.7) and Sacramento CSA (182.5). San Diego MSA shows the smallest ratio (114.9). These patterns are consistent with their relative metropolitan size. The ratios of the median population density and median employment density are quite similar, but the ratio of the means is not; ratios are higher for Sacramento and San Diego, suggesting a more dispersed pattern of employment. That is, employment concentration is greater in the two larger CSAs.

Table 3. 3 Population and employment density descriptive statistics

Los Angeles

	Mean	Median	Min	Max
Pop. Density	3,604	2,806	0	35,021
Emp. Density	1,573	565	0	247,629

San Francisco

	Mean	Median	Min	Max
Pop. Density	3,871	2,859	11	44,681
Emp. Density	2,418	555	6	127,415

Sacramento

	Mean	Median	Min	Max
Pop. Density	1,695	1,670	3	6,628
Emp. Density	708	240	3	43,884

San Diego

	Mean	Median	Min	Max
Pop. Density	2,857	2,315	19	19,335
Emp. Density	910	353	8	40,600

3.3.2 Population and employment quartile statistics

We compare population and employment distribution among the four metropolitan areas by quartile density groups. Each quartile group contains an almost consistent number of spatial units.[2] These quartile groups are comparable due to the regularity of the spatial unit in the number of inhabitants. For the Los Angeles and San Francisco CSAs, we use Traffic Analysis Zones (TAZ), spatial unit of analysis for the following Freight Landscape tests. For the Sacramento and San Diego CSAs, we use Census Tracts. The US Census Bureau formulates census tract as a small geographical unit for statistical analysis that optimally has 4,000 people within a range of 1,200-8,000. Spatial size varies depending on the density of population.[3] Census tract delineation does not take employment into account, so we cannot say that employment is equivalently comparable. Traffic Analysis Zones (TAZ) are similar to census tracts in terms of size and variation with population density.

We also create sixteen quartile density group combinations by combining four population quartile groups with four employment quartile groups, as presented in Table 3.4. This matrix is the basis for

[2] They are 'almost' consistent in Los Angeles and San Francisco CSAs because we dropped a few spatial units that have no traffic data. They are consistent in Sacramento CSA and San Diego MSA.
[3] Geographic terms and concepts – Census Tract, U.S. Census Bureau (https://www.census.gov/geo/reference/gtc/gtc_ct.html)

our models estimated in Chapter 4. We compare and present characteristics of population quartile groups, employment quartile groups, and quartile group combinations.

Table 3. 4 Development density matrix

Quartile groups	Population 1st Q	Population 2nd Q	Population 3rd Q	Population 4th Q
Employment 1st Q	P1 | E1	P2 | E1	P3 | E1	P4 | E1
Employment 2nd Q	P1 | E2	P2 | E2	P3 | E2	P4 | E2
Employment 3rd Q	P1 | E3	P2 | E3	P3 | E3	P4 | E3
Employment 4th Q	P1 | E4	P2 | E4	P3 | E4	P4 | E4

3.3.2.1 Population Density

Table 3.5 gives the average and distribution of population density quartiles for the four metro areas. Figure 3.3 graphs the population quartile mean values for each metro area and illustrates the large differences in overall distribution across the four metro areas. Figures 3.4 a-d map the population density quartiles. The Los Angeles and San Francisco CSAs have similar population distributions. The mean, minimum, and maximum density values of each quartile group are similar. The San Diego MSA has both a higher mean for the lowest quartile and lower mean for the highest quartile, indicating a more homogeneous overall distribution. Sacramento stands out as notably lower density throughout.

Table 3. 5 Population density quartiles

Los Angeles

Quartile	N of zones	Mean	Min	Max
P1	948	529	0.0	1,275
P2	947	2,050	1,275	2,806
P3	947	3,647	2,808	4,726
P4	947	8,192	4,728	35,021

*** N of quartiles is not the same, due to the elimination of zones with no traffic data.

San Francisco

Quartile	N of zones	Mean	Min	Max
P1	350	691	11	1,398
P2	349	2,189	1,399	2,857
P3	350	3,630	2,861	4,657
P4	349	8,985	4,666	44,681

Sacramento

Quartile	N of zones	Mean	Min	Max
P1	125	293	3	739
P2	125	1,205	744	1,669
P3	125	2,059	1,672	2,507
P4	125	3,222	2,516	6,628

San Diego

Quartile	N of zones	Mean	Min	Max
P1	150	786	19	1,350
P2	149	1,808	1,353	2,310
P3	150	3,037	2,319	3,698
P4	149	5,812	3,720	19,335

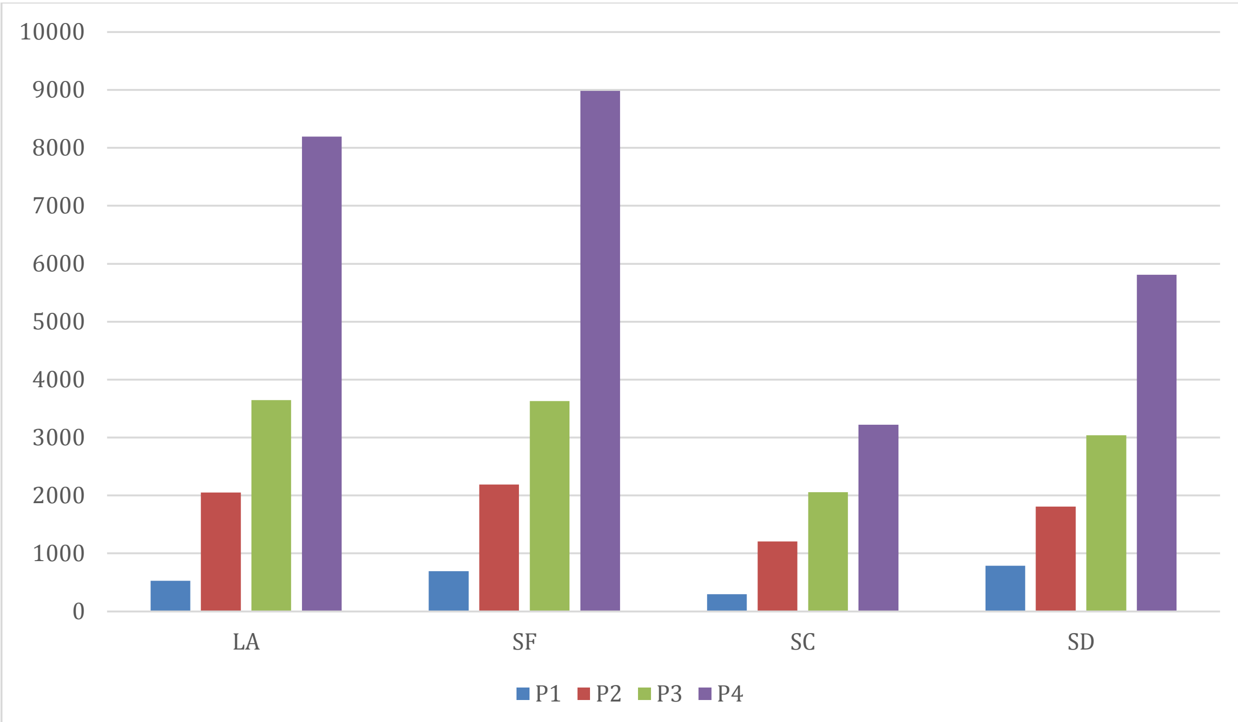
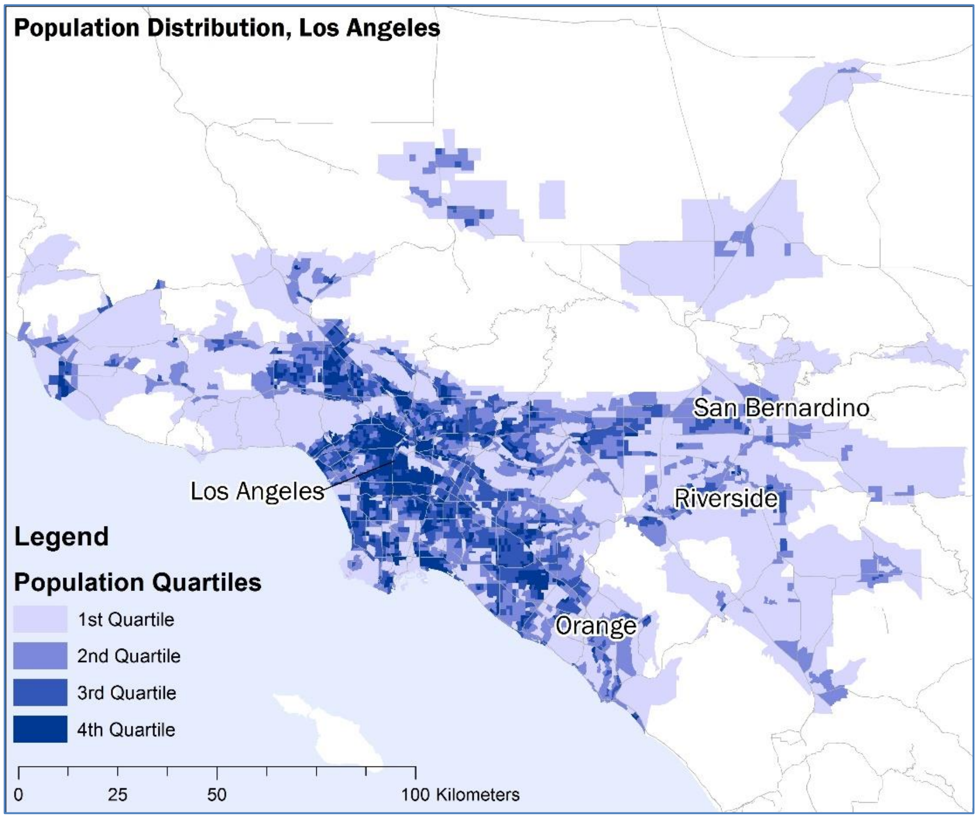
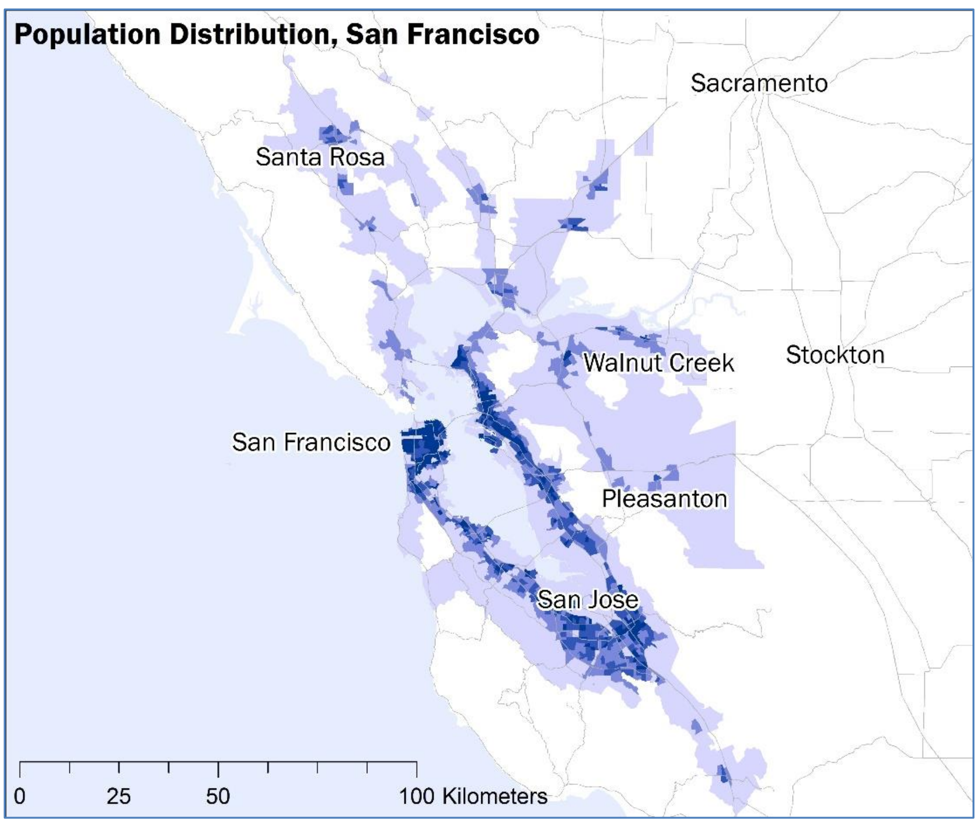
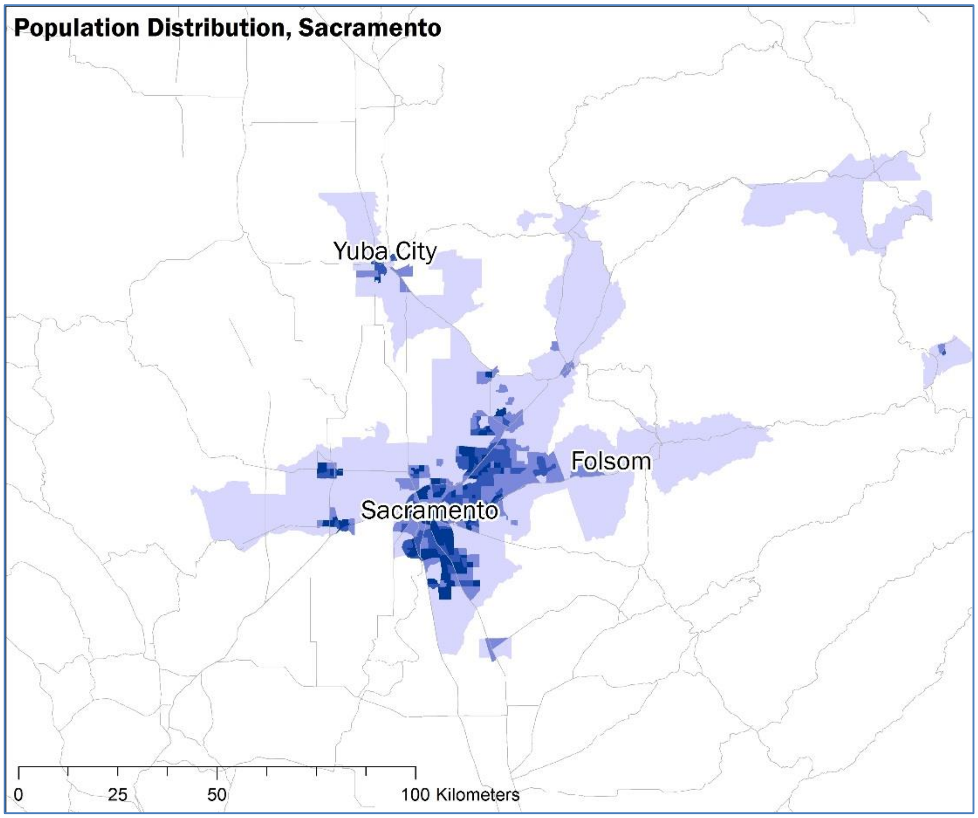


Figure 3. 3 Population quartile mean density

The figures show different population density patterns. In Los Angeles, population is spread throughout a large core area, with a corridor of higher density that approximates the main north-south freeways through the region. In San Francisco, population density is concentrated around the Bay. The geographic constraints – bay and mountain – define development patterns in this region. In Sacramento, population density is concentrated around the central city. The population density pattern is more irregular in San Diego, with the highest densities along the coast. In all cases, lower population density extends from the core along major highway corridors.


Population Distribution, Los Angeles
San Bernardino
Los Angeles
Riverside
Orange
Legend
Population Quartiles
1st Quartile
2nd Quartile
3rd Quartile
4th Quartile
0
25
50
100 Kilometers


Population Distribution, San Francisco
Sacramento
Santa Rosa
Walnut Creek
Stockton
San Francisco
Pleasanton
San Jose
0
25
50
100 Kilometers



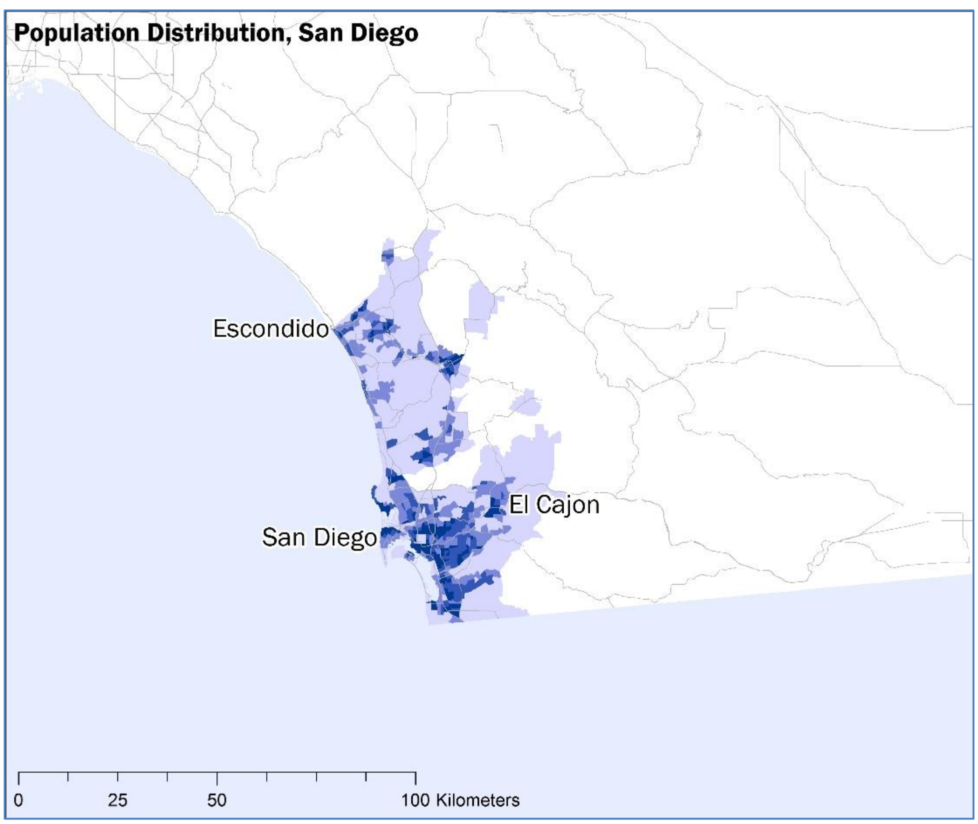


Figure 3. 4 a-d Population density quartiles of metro areas

3.3.2.2 Employment Density

Table 3.6 gives the average and distribution of employment density quartiles for the four metro areas, and Figure 3.5 graphs the quartile mean values. Figures 3.6 a-d map the employment density quartiles. There are several observations to be drawn from the table and figures. First, concentration of employment is observed throughout, but is most pronounced for San Francisco. However, although the San Francisco average for Q4 is notably higher than for Los Angeles, the maximum density is nearly twice as high in Los Angeles. Both metro areas have concentrated employment, but the pattern of concentration is different. Third, average employment density for every quartile is notably lower for Sacramento and San Diego, and the maximum density values are less than half of San Francisco's.

Table 3. 6 Employment density quartiles

Los Angeles

Quartile	N of zones	Mean	Min	Max
E1	948	93	0	207
E2	947	372	207	565
E3	947	883	566	1,307
E4	947	4,946	1,308	247,629

San Francisco

Quartile	N of zones	Mean	Min	Max
E1	350	116	6	234
E2	349	390	234	555
E3	350	848	555	1,316
E4	349	8,330	1,327	127,415

Sacramento

Quartile	N of zones	Mean	Min	Max
E1	125	35	3	83
E2	125	157	86	240
E3	125	388	241	605
E4	125	2,252	606	43,884

San Diego

Quartile	N of zones	Mean	Min	Max
E1	150	71	9	132
E2	149	237	132	352
E3	150	590	354	862
E4	149	2,752	863	40,600

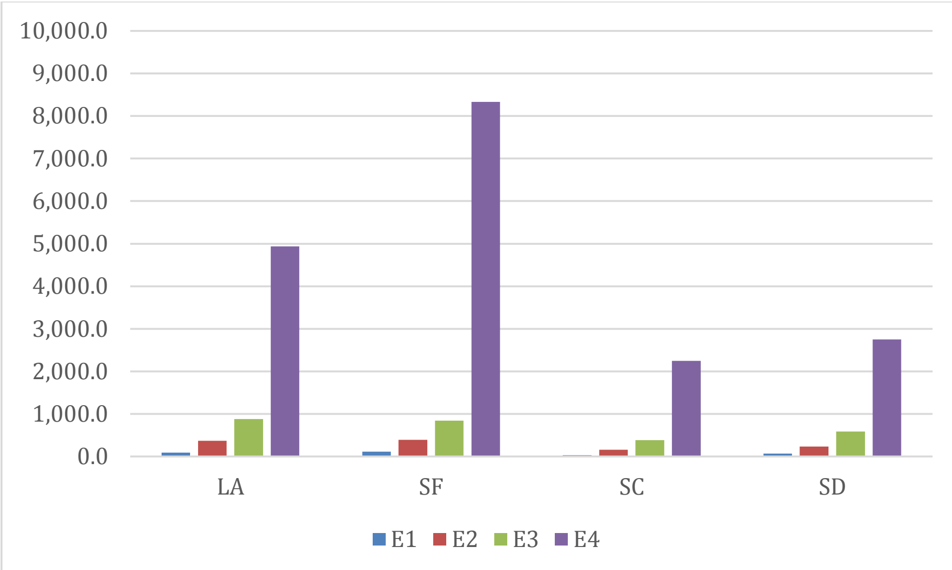
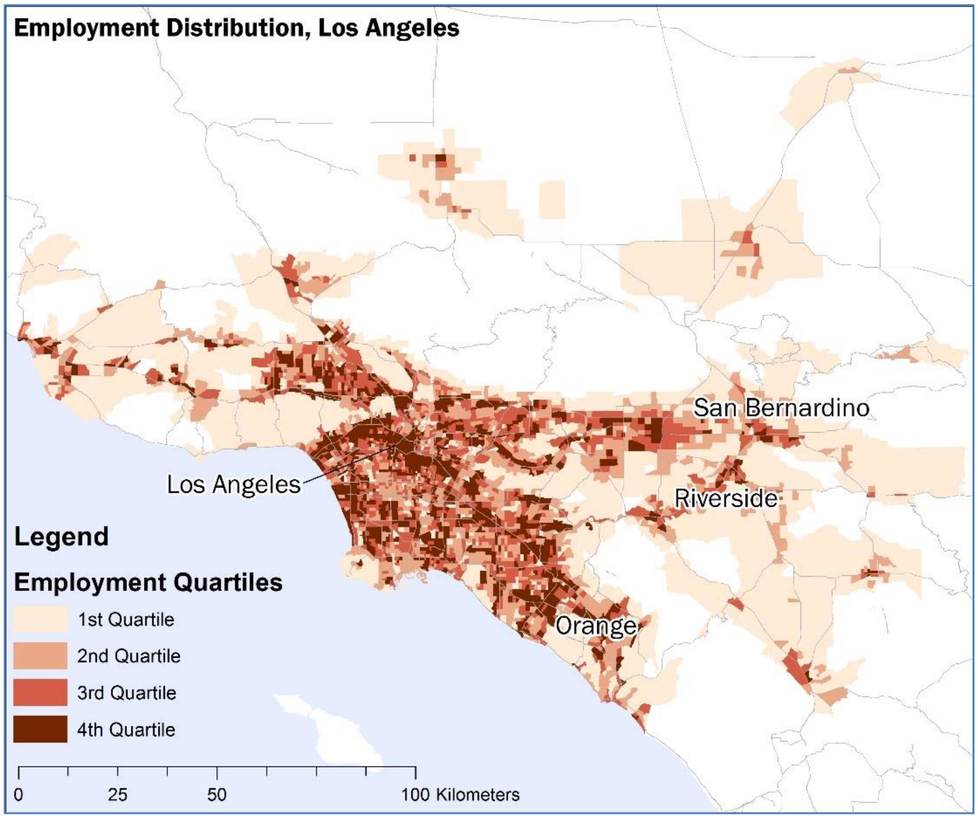
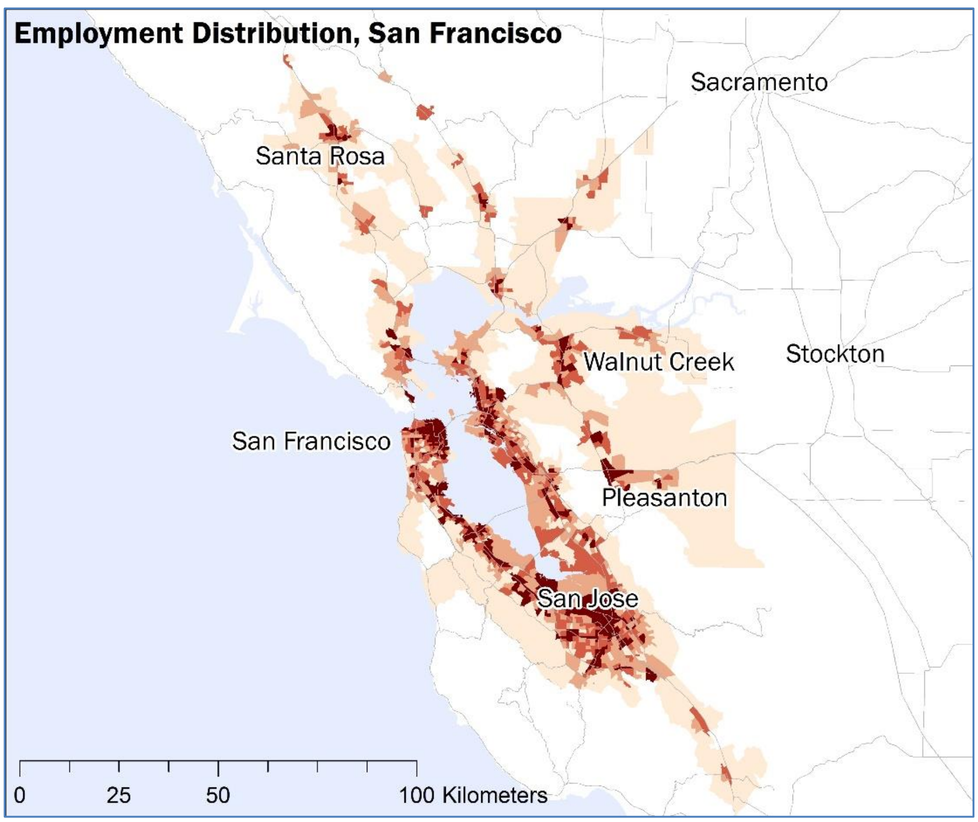
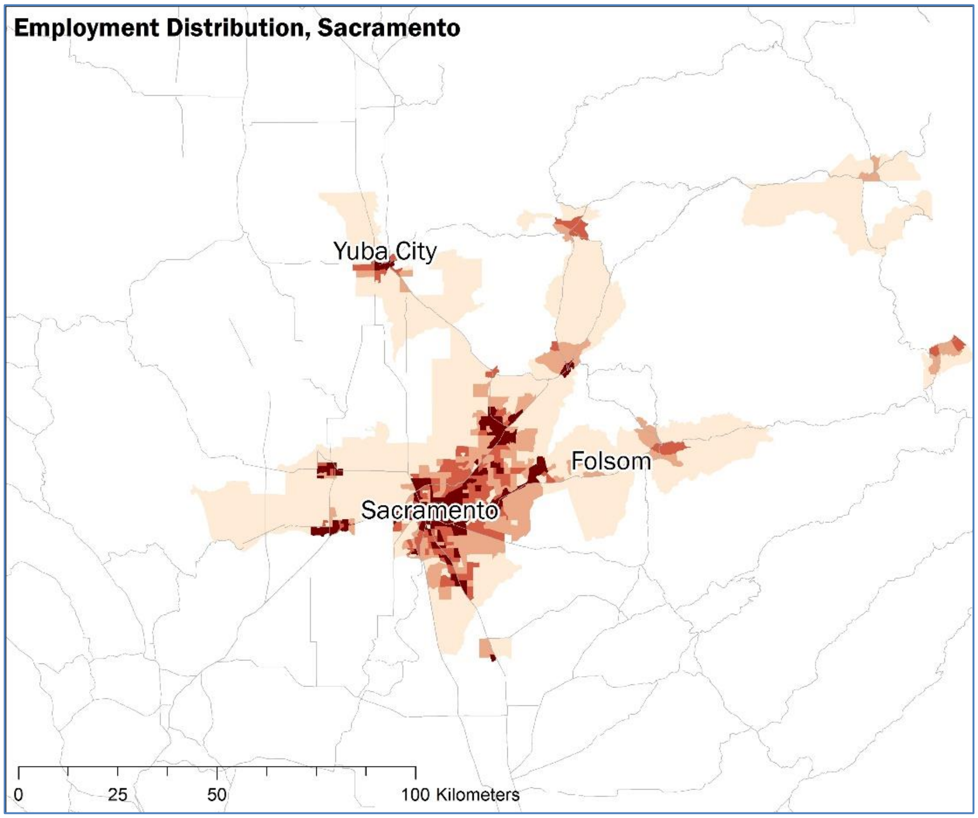


Figure 3. 5 Employment quartile mean density

Again, the four metropolitan areas show distinctive employment distribution patterns. In Los Angeles, similar to population, employment is spread throughout the region with a clear pattern of multiple employment concentration clusters There are corridors of high employment density along major highways, as well as large clusters in the Los Angeles downtown and in Orange County. San Francisco's unique geography predetermines employment distribution to locate along the narrow corridors of the Bay Area. Basically, employment co-locates with population. In Sacramento, most employment is concentrated in the central area with a few subcenters nearby. Similar to population, employment locates along highway corridors. In San Diego, the largest concentration of high employment density is north of downtown San Diego, in the area near a major university and bio-tech industry hub. As with Los Angeles, employment tends to locate along major highway corridors.


Employment Distribution, Los Angeles
San Bernardino
Los Angeles
Riverside
Orange
Legend
Employment Quartiles
1st Quartile
2nd Quartile
3rd Quartile
4th Quartile
0
25
50
100 Kilometers


Employment Distribution, San Francisco
Sacramento
Santa Rosa
Walnut Creek
Stockton
San Francisco
Pleasanton
San Jose
0
25
50
100 Kilometers



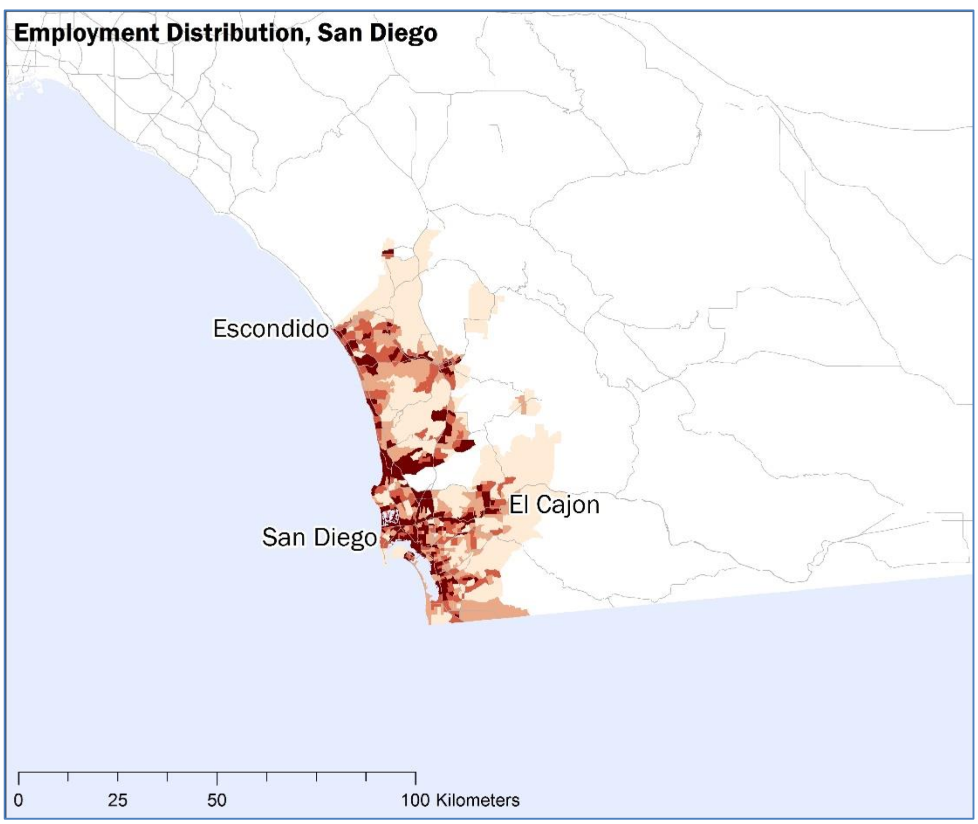


Figure 3. 6 a-d Employment density quartiles of metro areas

3.3.2.3 Development Density

The next step in our analysis is to generate the development density matrix per Table 3.5 and 3.6 above. We count the number of tracts or TAZs that meet the criteria of each category, and then calculate the share of tracts or TAZs that fall into each category. Table 3.7 gives the share of tracts or TAZs in each category for each metro area. Figures 3.7 a-d give the same information as bubble graphs. If there were a homogeneous distribution across all categories, each bubble would be of the same size.

Table 3. 7 Development density distribution

Los Angeles

Quartile	P1	P2	P3	P4
E1	14.9%	5.8%	2.9%	1.5%
E2	3.2%	7.9%	8.0%	5.8%
E3	2.6%	5.5%	8.5%	8.5%
E4	4.4%	5.8%	5.6%	9.2%

San Francisco

Quartile	P1	P2	P3	P4
E1	14.3%	6.4%	3.7%	0.7%
E2	4.2%	6.9%	8.3%	5.7%
E3	2.9%	5.9%	7.7%	8.4%
E4	3.7%	5.8%	5.4%	10.2%

Sacramento

Quartile	P1	P2	P3	P4
E1	16.6%	5.2%	0.8%	2.4%
E2	4.4%	7.6%	6.6%	6.4%
E3	1.8%	5.2%	8.8%	9.2%
E4	2.2%	7.0%	8.8%	7.0%

San Diego

Quartile	P1	P2	P3	P4
E1	12.4%	4.9%	6.2%	1.7%
E2	6.2%	7.0%	6.5%	5.2%
E3	2.5%	8.2%	6.0%	8.4%
E4	4.0%	4.9%	6.4%	9.7%

If population and employment density were perfectly spatially correlated, our bubble graphs would have large circles down the diagonal, and other cells would be empty. This is not the case; few cells are empty, and the bubbles are of comparable size from P2/E2 to P4/E4. That is, population and employment are mixed, but there are many different versions of mixing. The single largest bubble in all cases is P1/E1; the largest share of zones have both lowest population and lowest employment density. These are the suburban residental areas of each metro area. The second largest buble for all but Sacramento is the highest density combination, P4/E4. This is consistent with employment concentration, but also with the observation that even in the largest employment centers there is substantional mixing of population.

Few zones or tracts have high population density but low employmen density. This is reasonable: population serving economic activity locates in concert with the population. Zones with high population density but low employment density suggest a lack of basic consumer services. On the other hand, it is less uncommon to see employment dominant zones. Again this is reasonable. Industrial areas tend to "zone out" residential land use due to externalitles.

There are differences in the distribution across the four metro areas. Los Angeles is the only case where the largest share for each column is on the diagonal, suggesting more correlation of population and employment density than the other metro areas. However, this is not the case for each row. Overall, there is substantial mixing of population and employment at varying combinations of higher densities. Given these differences, perhaps the most striking observation is the similarity of the distributions, despite the large differences in size, geography and function of these metro areas.

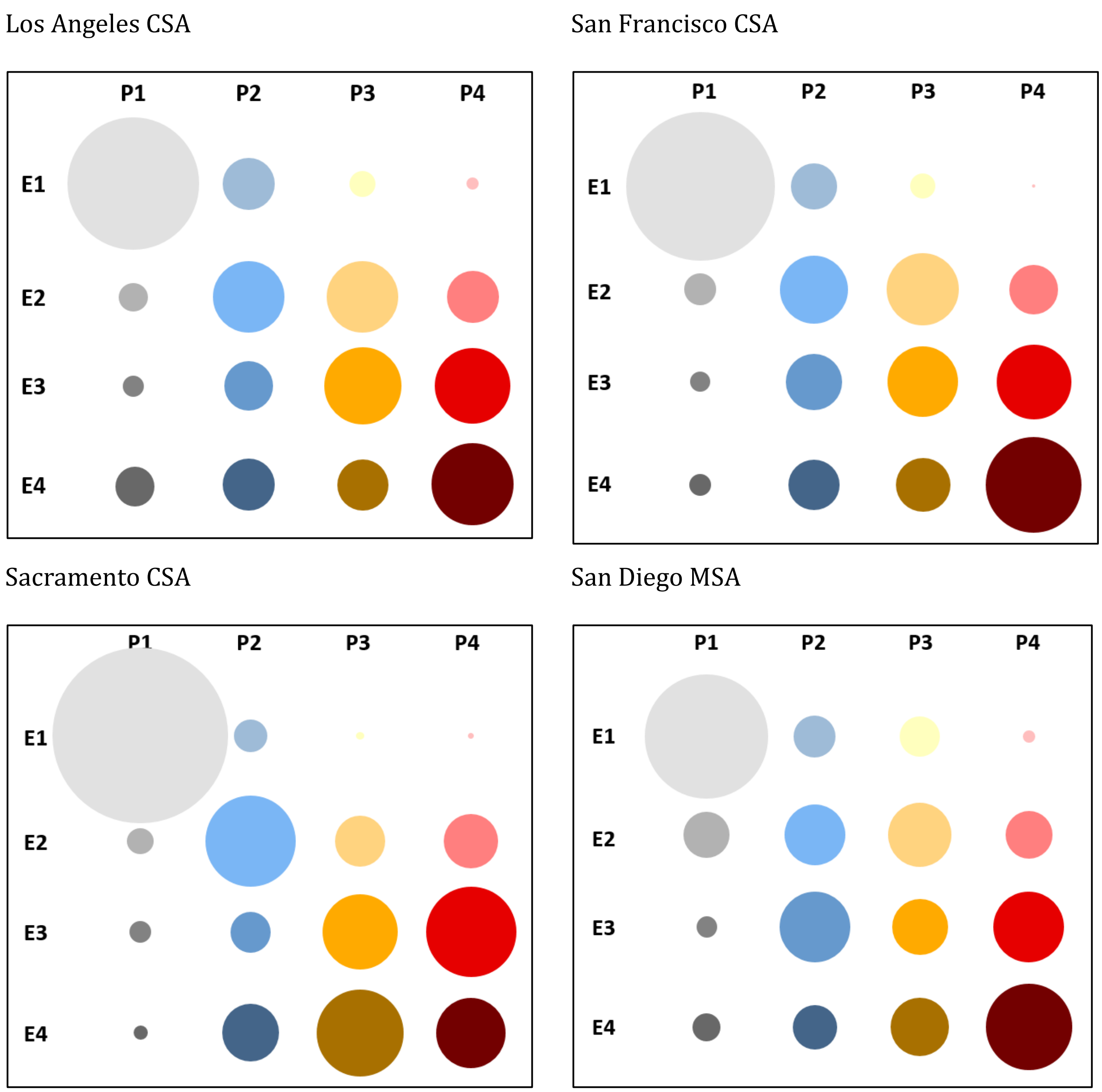


Figure 3. 7 a-d Bubble graphs showing the share of tracts or TAZs in each category for each metro area

The development density matrix reveals unique spatial structure. Figures 3.8 through 3.14 map development density for the four metro areas. High employment-high population zones (P4|E4), employment-dominant zones (P1|E4) and low employment-low population zones (P1|E1) are clearly visible, and their distribution is different across four metro areas. In Los Angeles there is a general concentration in the downtown area core, with other concentrations to the north, east and south, consistent with the polycentric structure of the region. In Figure 3.9, a long corridor of high employment and high population (P4|E4, P3|E4, P4|E3) is evident along Downtown LA-Hollywood-Westwood-Santa Monica. This is the largest population-employment concentration in the region. Right next to Downtown LA is the old industrial zone, where two major truck-rail intermodal facilities are located. Figure 3.10 shows employment-dominant zones along major highway corridors, with a large employment cluster surrounding one of the region's major airports. Development density in San Francisco is consistent with employment and population, and is mainly clustered around the bay (Figure 3.11). High employment-high population and employment dominant zones are clearly visible. Figure 3.12 shows downtownSF with its concentration of high employment-high population. San Jose has a large cluster of employment dominent zones, the – Silicon Valley high tech industry cluster. Sacramento has a roughly monocentric pattern of development density (Figure 3.13). San Diego shows two different patterns (Figure 3.14). In the north, there is relatively little mixing of employment and population density. The downtown area has higher density and more mixing of population, and this pattern extends south along the major highway corridor.

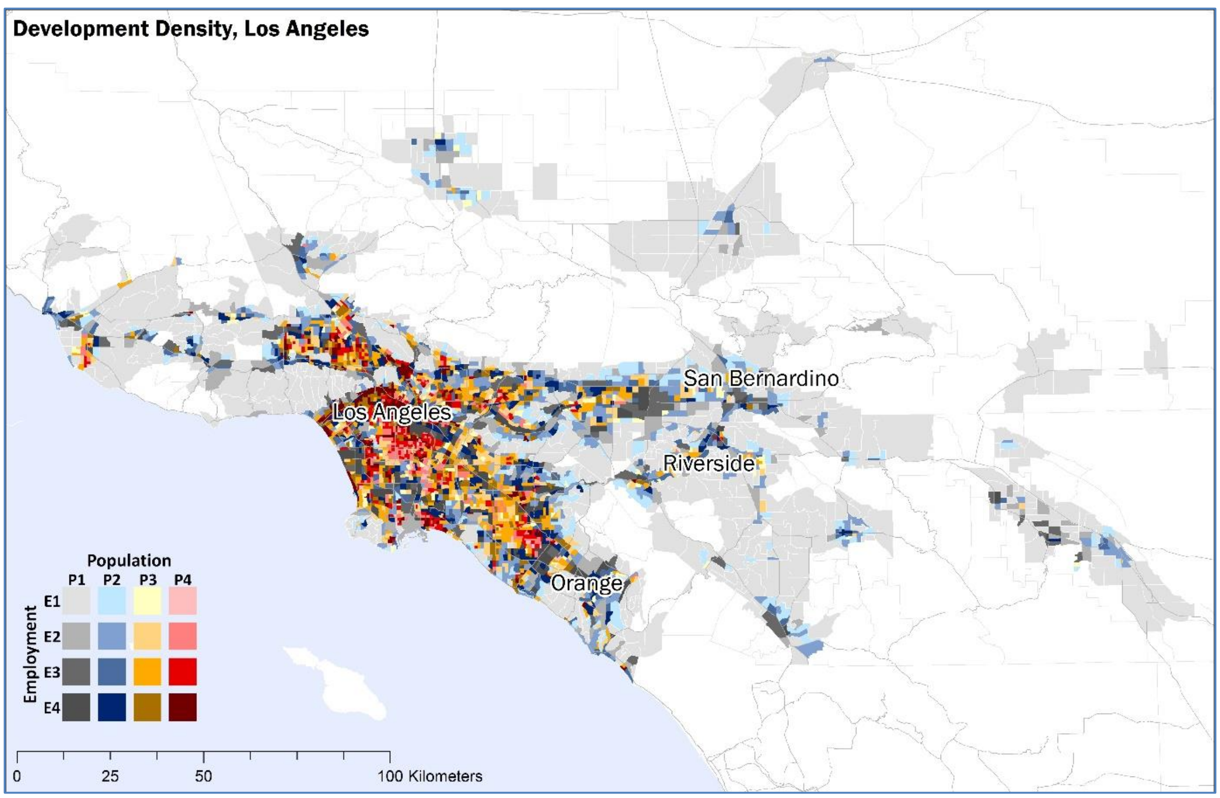


Figure 3. 8 Development density map of Los Angeles region

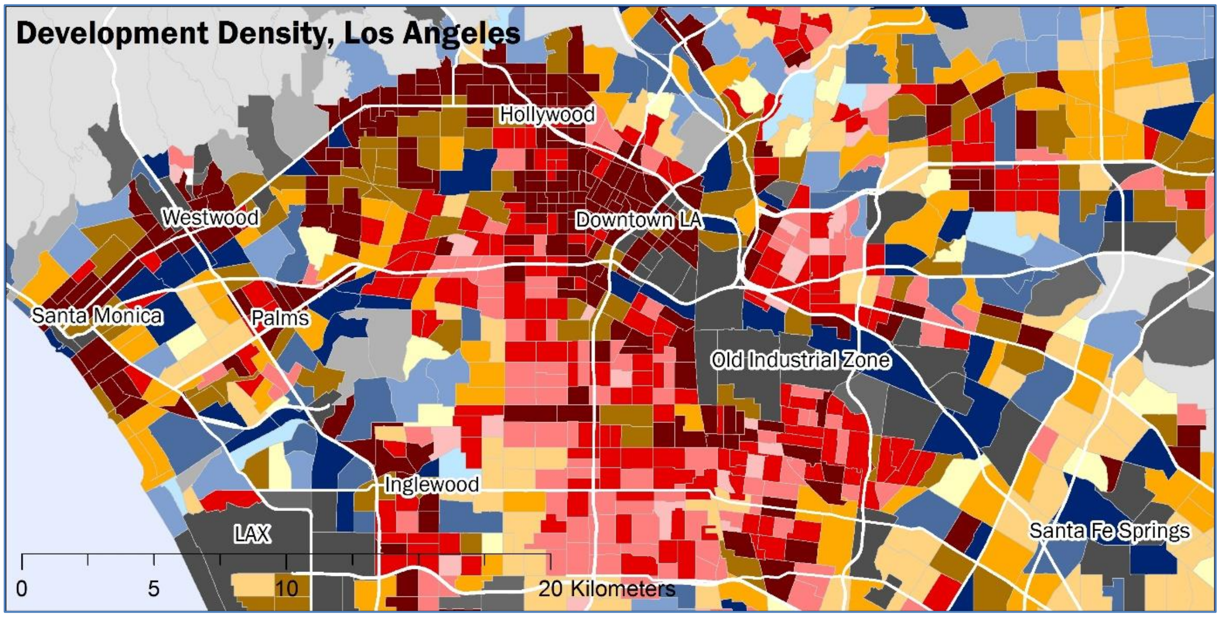


Figure 3. 9 Downtown LA-Hollywood-Westwood-Santa Monic Corridor

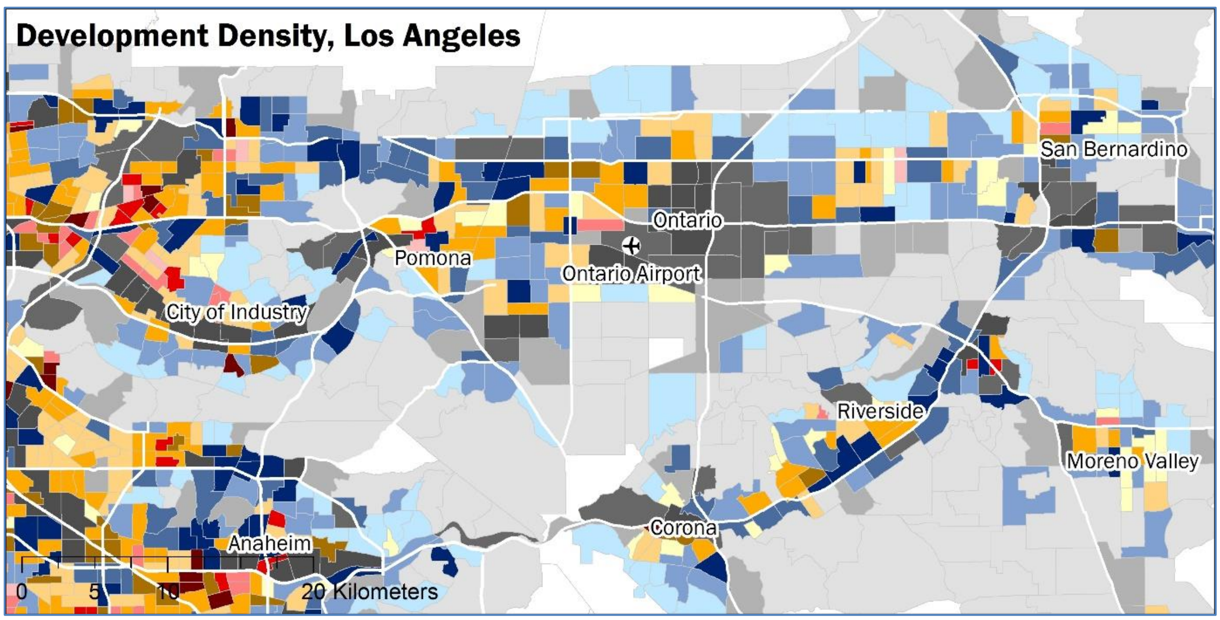


Figure 3. 10 Employment-dominant zones along major highway corridors

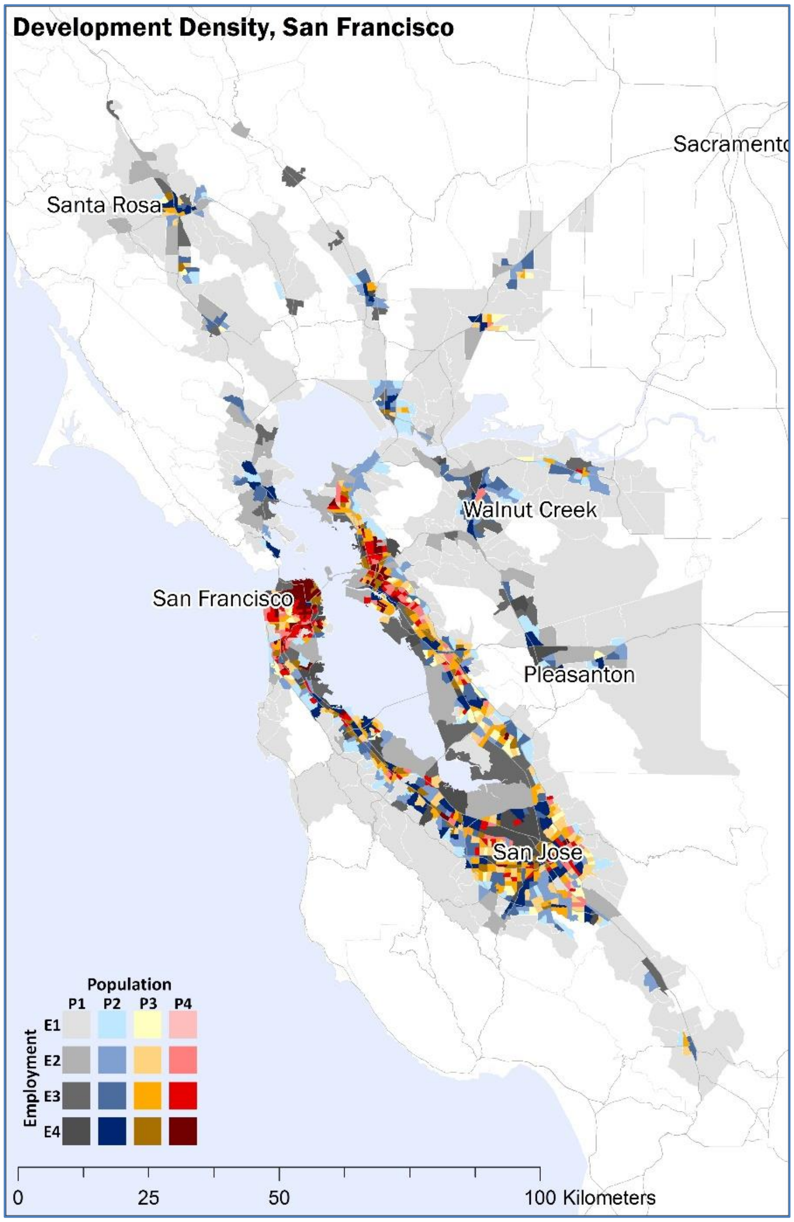


Figure 3. 11 Development density map of San Francisco region

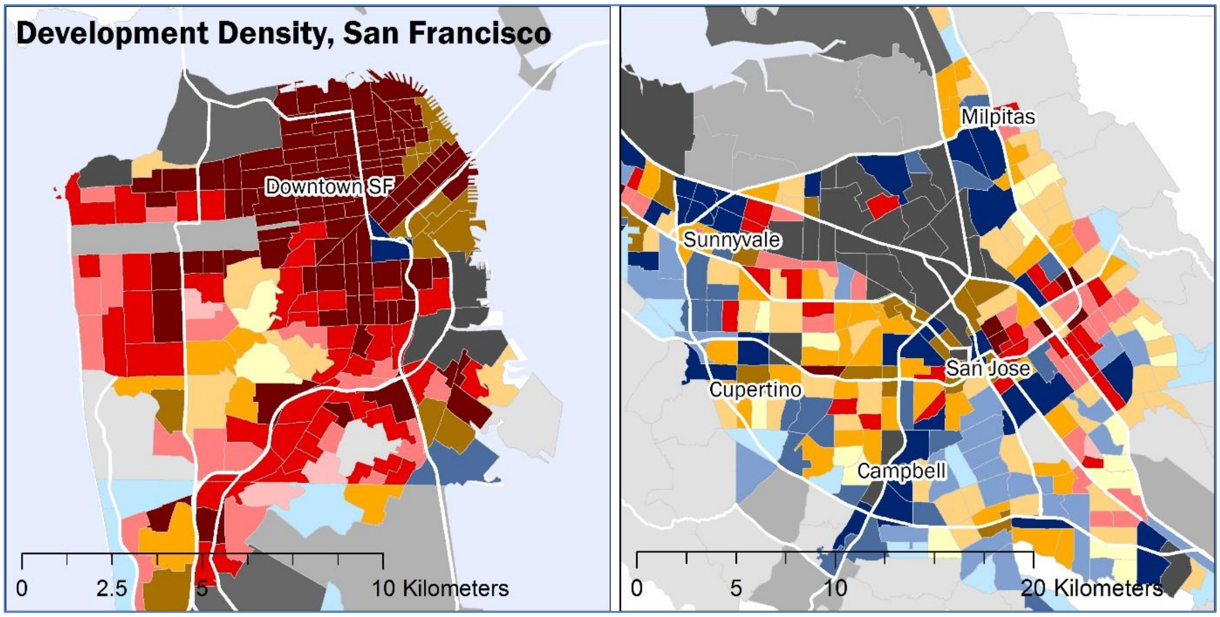


Figure 3. 12 Downtown San Francisco and San Jose

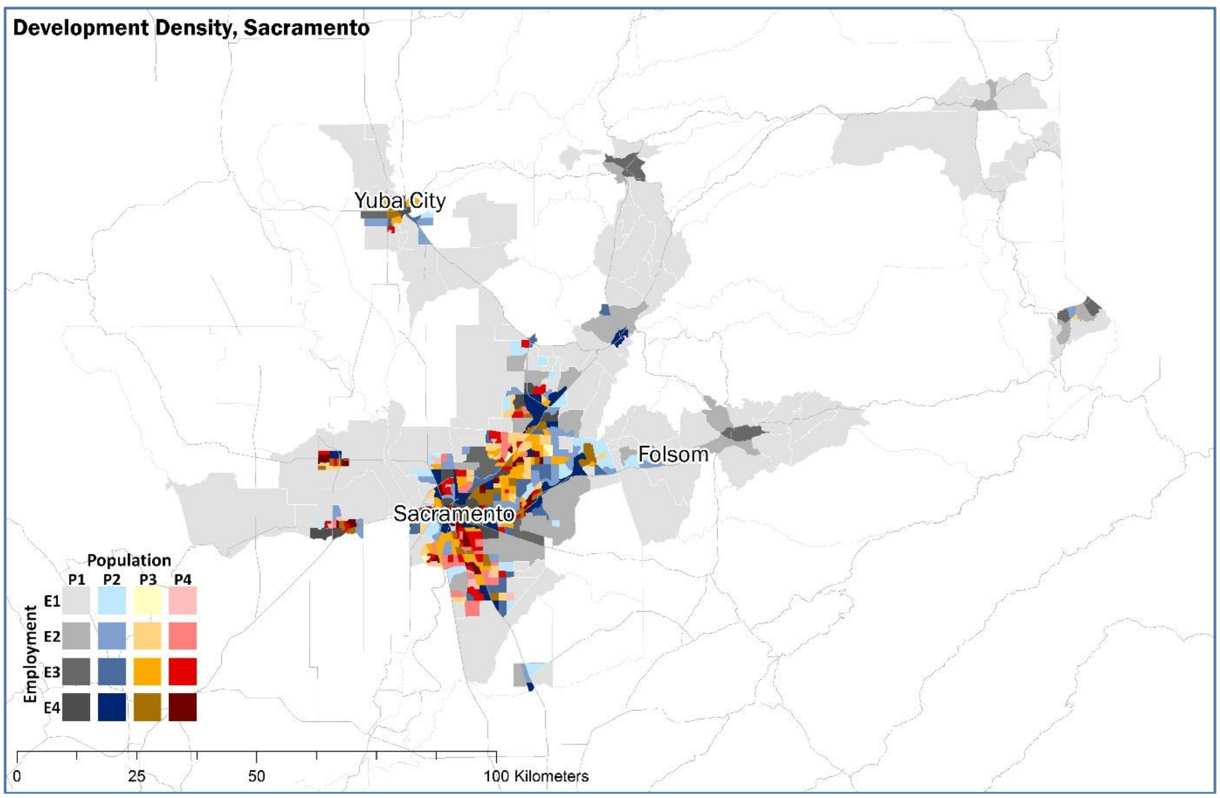


Figure 3. 13 Development density map of Sacramento region

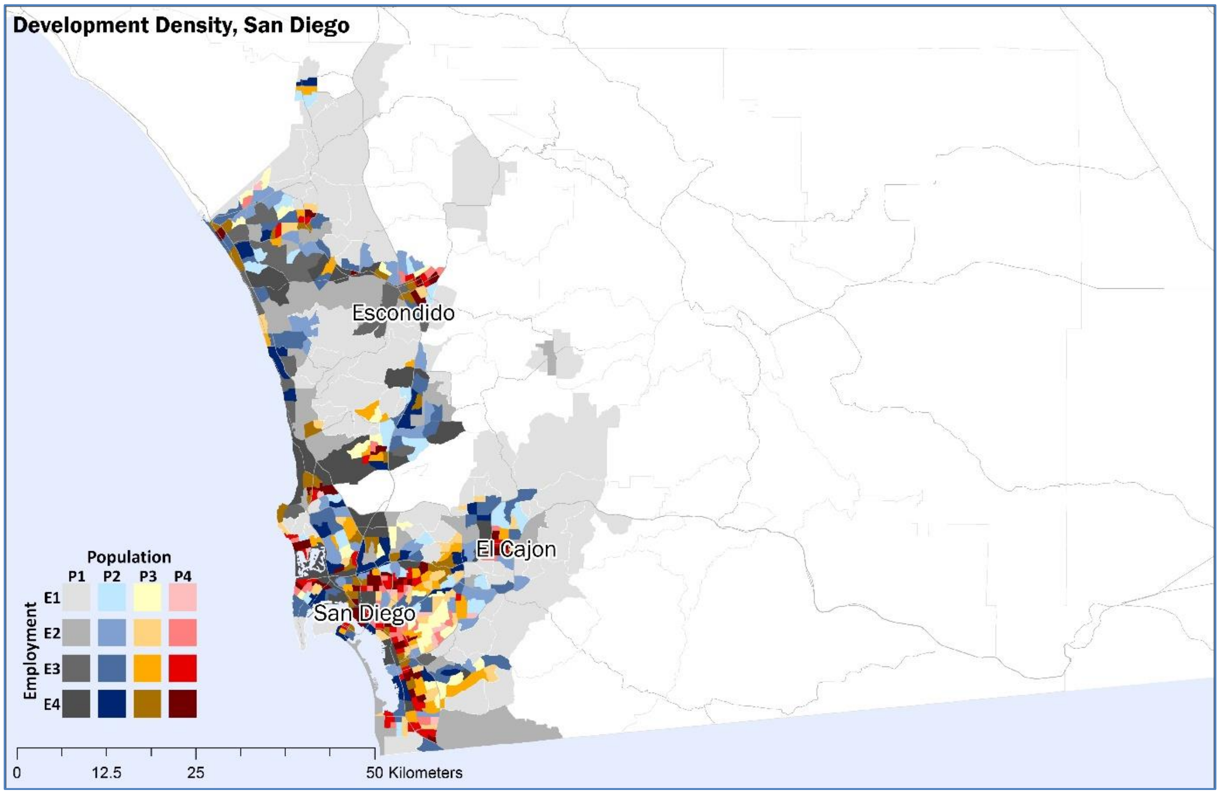


Figure 3. 14 Development density map of San Diego region

3.4 Freight transportation infrastructure, development density and freight flow

In this section, we describe major freight infrastructure in comparison with development density. We include major highway networks, container seaports, cargo service airports, and intermodal facilities. Then we describe freight flows with respect to internal, domestic and international trade.

3.4.1 Major freight transportation infrastructure and development density

Los Angeles CSA

The Los Angeles CSA is one of the largest freight hubs in the U.S.: the largest containerized port complex, seventh busiest cargo airport system, and busiest freight rail system. [4]

Los Angeles CSA has three sea ports: Port of Los Angeles (POLA), Port of Long Beach (POLB), and Port of Hueneme. POLA and POLB are co-located in San Pedro Bay. These two ports handled 40% of all U.S. containerized imports in 2013 (12.8 million TEUs, 90% from East Asia). Port of Hueneme in Santa Barbara Channel handles automobiles (Roll-On/Roll-Off) and fresh produce. It is the 4th largest port in California by tonnage.

[4] Caltrans Freight Planning Fact sheet – District 7

Cargo service airports include LAX (LA International), ONT (Ontario International), and LGB (Long Beach). LAX handled 4.3 billion lbs. of landed air cargo in 2014, the largest in California. ONT handled 2.4 billion lbs (13th in the U.S.), and LGB 164 million lbs (98th in the U.S.). These airports represent 54% of the total landed air cargo tonnage of California. According to Caltrans, LGB's landed weight shrank by half 2003-2011 because most larger volume cargo volumes are trucked to LAX or ONT. ONT is the West Coast regional air hub for United Parcel Service (UPS). [5]

LA CSA has six intermodal facilities: BNSF LA Hobart, BNSF San Bernardino, BNSF OIG, UP Los Angeles, UP LATC, UP City of Industry, and UP ICTF. BNSF's Hobart Yard is the largest intermodal rail yard in the U.S. Over 1 million containers are transloaded to over 40,000 locomotives per year. UP ICTF, located near the ports, is a container loading site for trains traveling to the LA rail yards via the Alameda Corridor, a fully grade separated rail corridor. BNSF San Bernardino's Transcontinental Route is the primary freight rail route that runs to Chicago, Memphis and Kansas City. We present the freight infrastructure system in Figure 3.15.

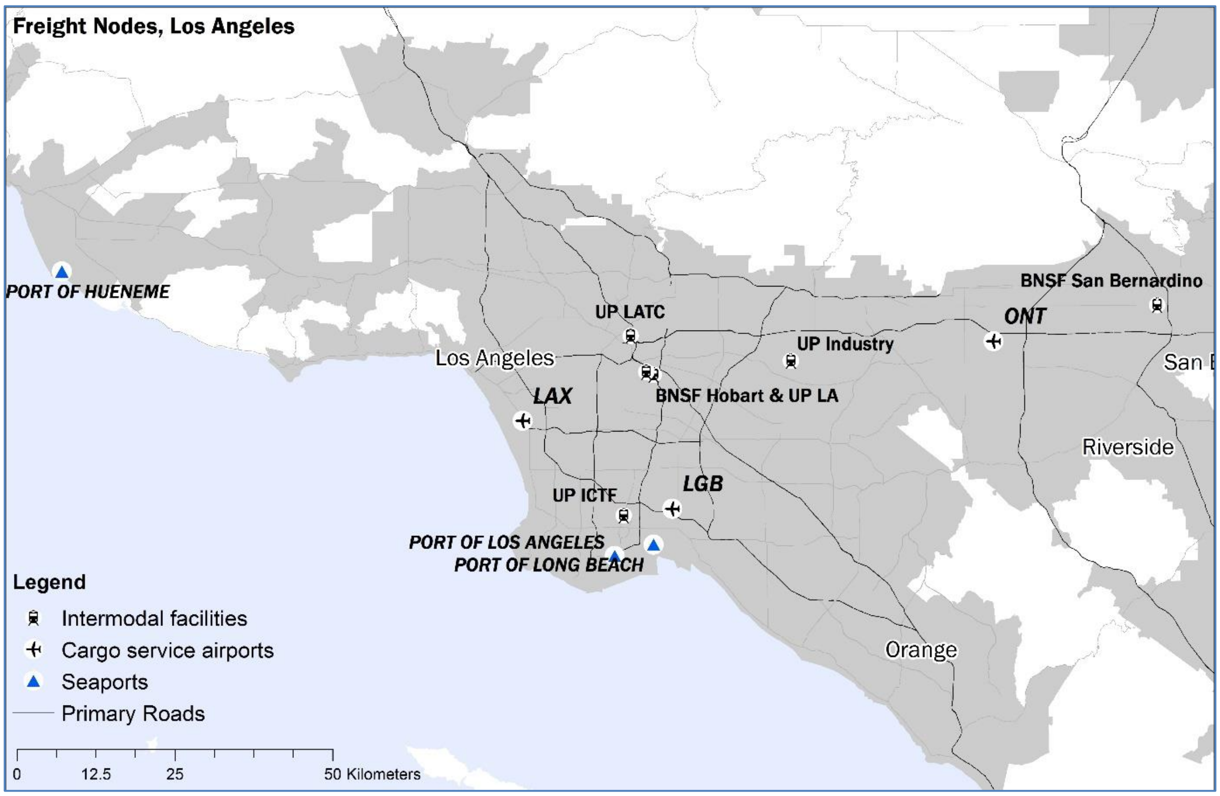


Figure 3. 15 Freight nodes in LA

In Figure 3.16, we map employment-dominant zones (P1|E4) and the major freight nodes. As discussed earlier, we expect employment dominant zones to represent industry sectors that generate externalities (noise, freight traffic and associated pollution) and are therefore not attractive to residential neighborhoods. It can be seen that these zones are located around the major cargo airports and the railyards in the downtown industrial zone. Other zone are located along freeway corridors. In some cases, zoning plays a role. For example, the Irvine area is a large commercial complex that was zoned for such development.

[5] Federal Aviation Administration – All-Cargo Data for U.S. Airports 2014

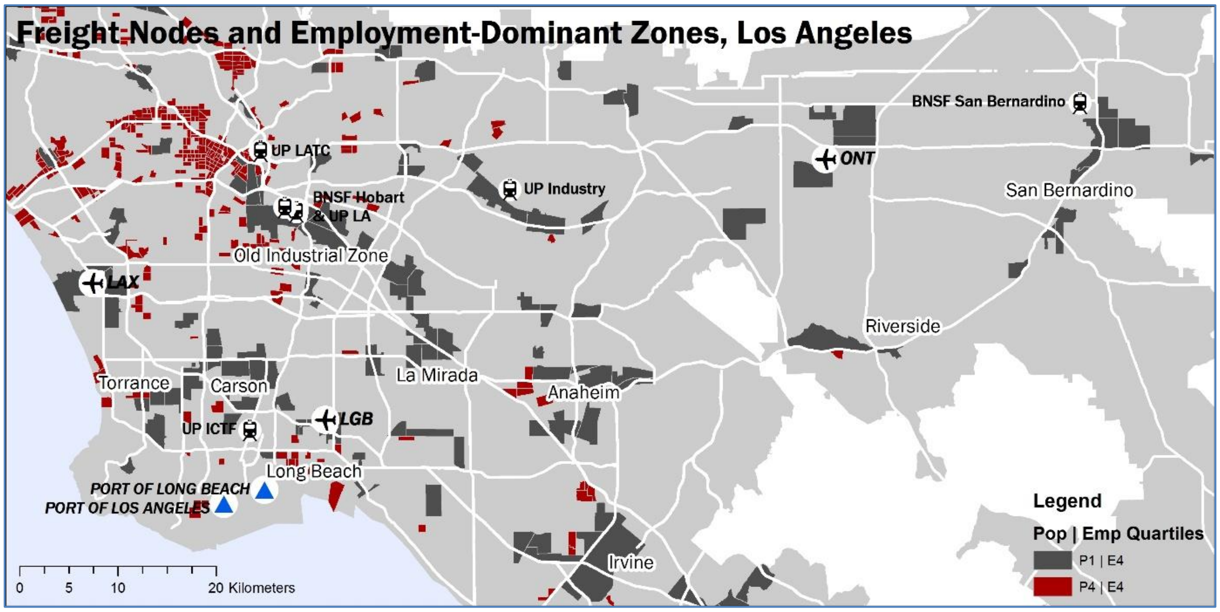


Figure 3. 16 Employment-dominant zones and major freight nodes in LA

San Francisco CSA

Freight infrastructure in San Francisco is not as extensive as that of Los Angeles. The seaport system in San Francisco Bay Area includes the region's principal water-trade gateway Port of Oakland as well as several smaller ports. The Port of Oakland is the largest, and handles nearly all Northern California container traffic. It has an intermodal facility jointly operated by BNSF and UP. Other ports handle dry/liquid bulk and break bulk cargo.

San Francisco has three cargo service airports: OAK (Metropolitan Oakland International), SFO (San Francisco International), and SJC (Norman Y. Mineta San Jose International). OAK handed 2.9 billion lbs. of landed air cargo in 2014 (11th in the U.S). FedEx has OAK as its Express Super Hub. SFO handled 1.2 billion lbs. (21st in the U.S.). SJC handled only 164 million lbs., due to limited capacity. We present the freight infrastructure system in Figure 3.17.

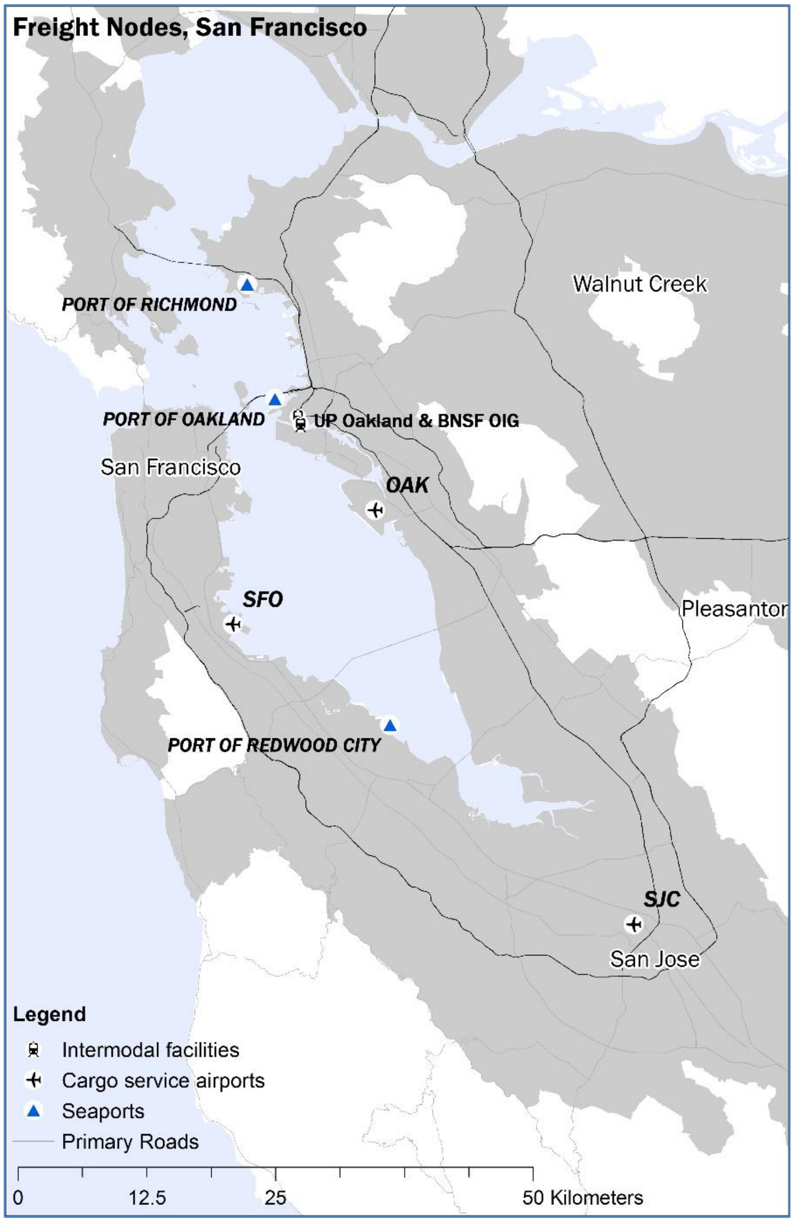


Figure 3. 17 Freight nodes in SF

Figure 3.18 shows employment dominant zones and the freight facilities. As in Los Angeles, we see that most such zones are located either around major facilities (airports or ports), or along freeway corridors. The co-location of employment-dominant zones (P1|E4) with major freight nodes is not as obvious as it is in Los Angeles. San Jose has the largest cluster, and like Irvine, is likely a result of commercial or industrial zoning.

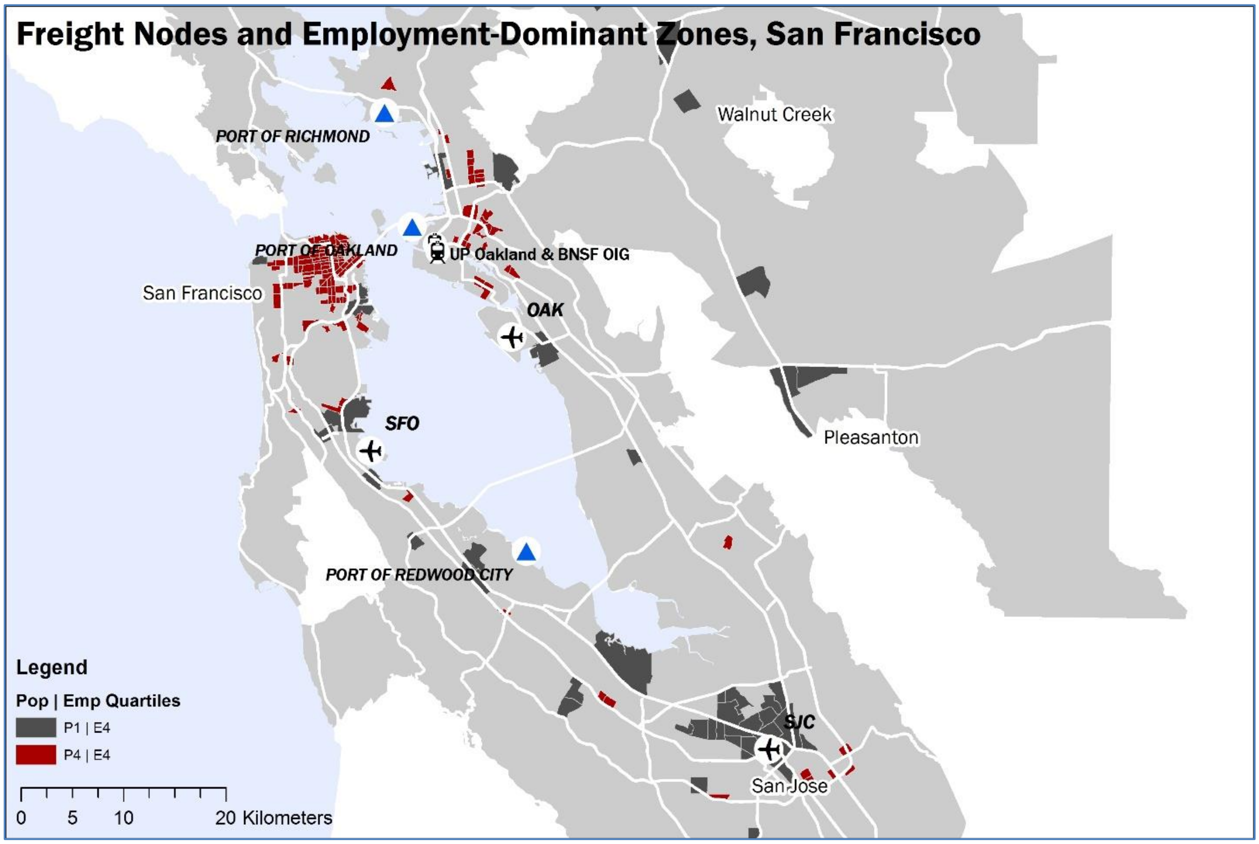


Figure 3. 18 Employment-dominant zones and major freight nodes in SF

Sacramento and San Diego

Sacramento and San Diego are far smaller metro areas and do not function as major trade nodes. Sacramento has an inland seaport that handles bulk and break bulk cargo, which is mainly agriculture and construction products. There are two cargo service airports. MHR (Sacramento Mather) handled 361 million lbs. landed air cargo , and SMF (Sacramento International) handled 287 million lbs landed air cargo in 2014 – together about one tenth of LA air cargo volume.

In San Diego, the Port of San Diego handled 43 thousand TEUs of containers in 2013 and 3.25 million deadweight ton of Roll-on/Roll-off cargo. SAN (San Diego International) handled 587 million lbs. landed air cargo in 2014, about the same as San Diego. San Diego has several Ports of Entry (POE) crossing the border between Mexico and the U.S. In particular, Otay Mesa POE on SR 905 is the busiest; it handles 1.4 million trucks and $20 billion worth freight in both directions per year, according to Caltrans. [6]

Figure 3.19 and 3.20 show freight facilities and employment dominant zones for Sacramento and San Diego respectively. In Sacramento there is colocation with the Port of Sacramento, but not the airports. In San Diego there is little evidence of colocation. This is likely due to the location of the airport and port next to downtown San Diego, where land is too valuable to support industrial uses. In north San Diego, the cluster around University City is another example of active zoning. Irvine, Silicon Valley, and University City were all developed from the 1980s, when separation of

[6] Caltrans Freight Planning Fact Sheet – District 11

commercial and residential activity was common planning practice. Generally, these zones are along freeway corridors, as in Los Angeles and San Francisco.

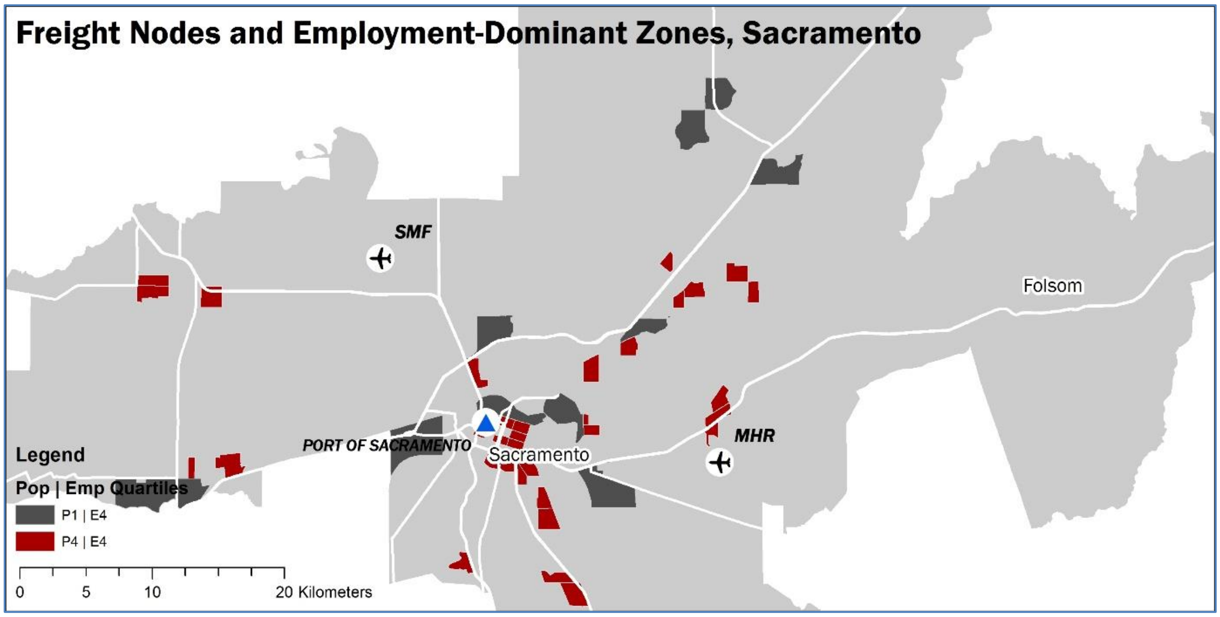


Figure 3. 19 Freight nodes in Sacramento

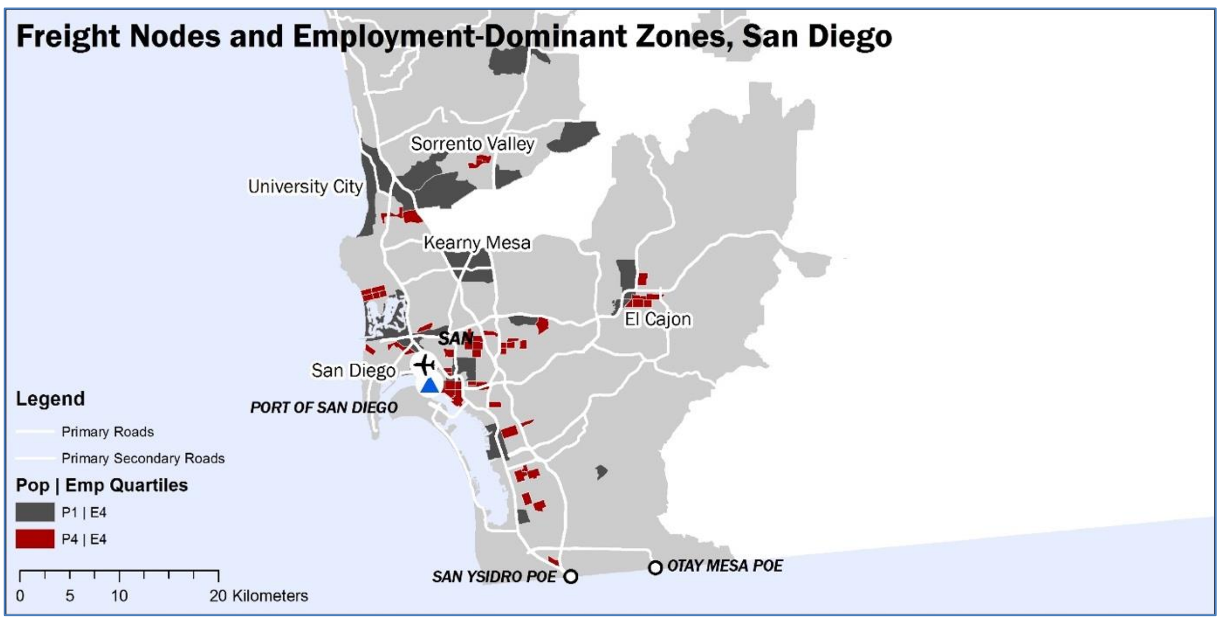


Figure 3. 20 Freight nodes in San Diego

3.4.2 Freight flows

As noted earlier, we were unable to obtain sub-metropolitan level freight flow data for San Diego and Sacramento. In this section we use the Commodity Flow Survey (CFS) data to make some general comparisons of freight flows across the four metropolitan areas. The Freight Analysis Framework (FAF) gives flows within and between the FAF regions based on CFS data. The FAF regions are the smallest geographic units for which CFS data are available. California has five FAF regions: Los Angeles, San Francisco, San Diego, Sacramento and Remainder of California; see Figure 3.21. The boundaries of the FAF Regions are based on MSA or CSA boundaries. However, part of the Sacramento CSA is outside of California, and hence is not included in the Sacramento CA FAF Region. FAF provides total flows, domestic flows, import flows and export flows that originate and enter each FAF region in 2007 (2012 data is still only available as provisional). Flow data with different modes, measures, and commodity categories are available in FAF as well.

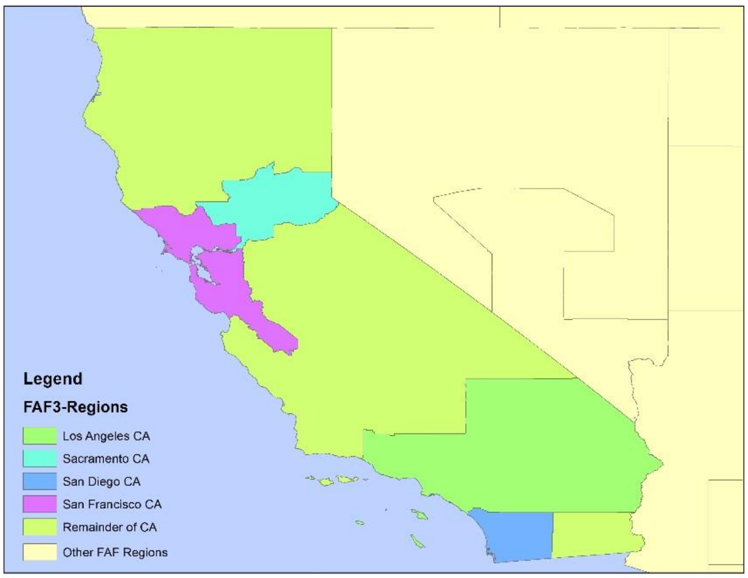


Figure 3. 21 Freight Analysis Framework Zones in California

Based on the CFS data in 2007, we rank all the FAF regions in the US according to the value of domestic commodity flows and foreign flows. A domestic flow is any flow that departs from the given zone and arrives in any other US zone, or that arrives in the given zone from any other US zone. Import and export flows have origins or destinations outside the US. With respect to domestic flows, the ranks (out of 123 FAF zones) are 1 for Los Angeles, 9 for San Francisco, 46 for San Diego, and 63 for Sacramento. With respect to foreign imports and exports, the ranks are 1 for Los Angeles, 6 for San Francisco, 49 for San Diego, and 78 for Sacramento.

Figure 3.22 gives internal, domestic, and foreign flows for each metro area. Internal flows follow the rank order of population or employment of each metro area. International flows are disproportionately small for San Diego and Sacramento. The role of Los Angeles as a trade center is quite obvious, with all types of flows markedly greater than those of San Francisco.

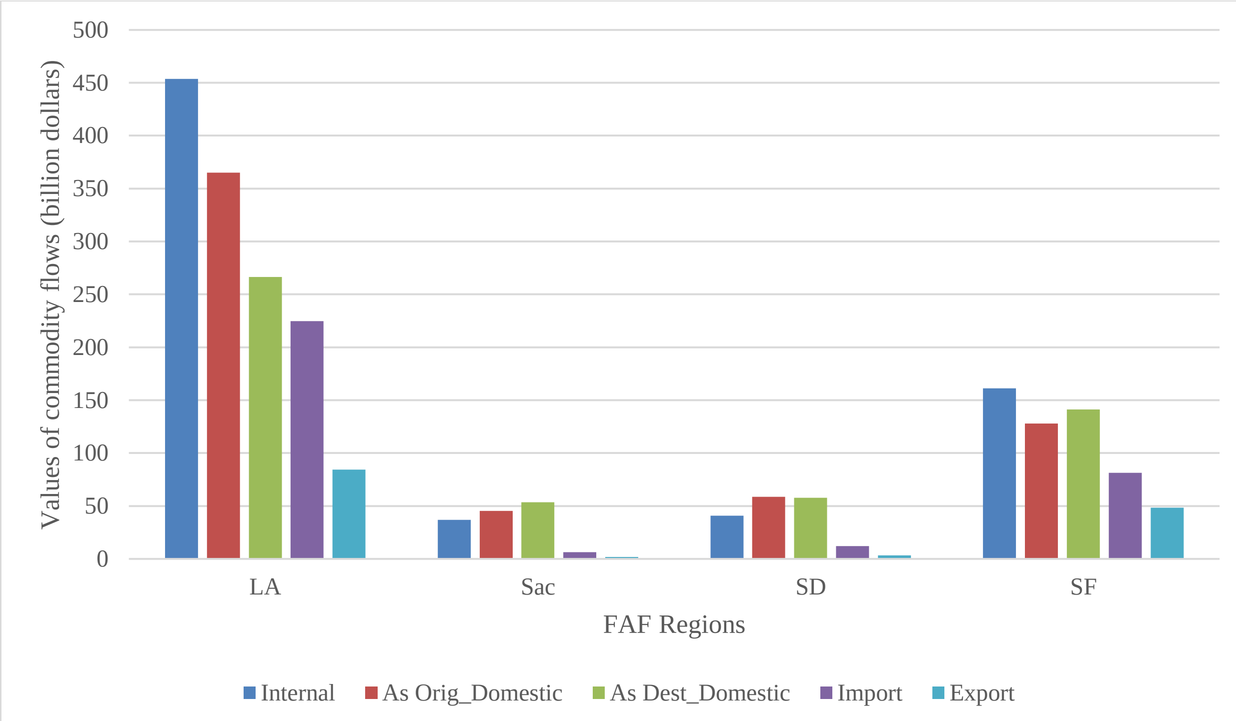


Figure 3. 22 The sizes of commodity flow types (by value) of the four FAF regions in 2007 (FAF 2007)

We compare commodity flow intensity between the four FAF regions by calculating per capita and per employee commodity flow (see Table 3.8). Total domestic flows and total export flows are selected as indicators. In terms of domestic flow intensity, the four FAF regions have comparable per capita domestic flow intensity, implying that domestic flows are essentially a function of the population size of a metro. The domestic flow values per employee in SF, SD and Sacramento are similar, too. However, the export flow intensity appear to vary greatly across the four regions. The per-capita and per-employee export flow values in LA and SF are far more than those in SD and Sacramento. The differences indicate that the four FAF regions have distinct roles in international trade. Regions more engaged in domestic or international trade should have more freight activity.

Table 3. 8 Comparison of commodity flow intensity across the four FAF regions in California

	Domestic flow (Million $)	Int'l flow (Million $)	Domestic flow per capita ($/person)	Int'l flow per capita ($/person)	Domestic flow per employee ($/employee)	Int'l flow per employee ($/employee)
LA	631,461	309,302	35331	17306	89764	43968
SF	99,038	8,333	37725	18196	85628	41301
SD	116,273	15,452	37564	4992	94510	12560
Sac	269,114	129,804	41013	3450	109031	9174

The LEHD has sector level data; we use one digit NAICS to compare industry mix across our metro areas. We expect that freight traffic is related to industry mix: regions with more manufacturing or trade activities should generate more freight than regions with more service activity. Figure 3.23 gives sector shares for the four metro areas. Los Angeles and San Francisco have higher shares of jobs in manufacturing sector (NAICS sector 3), consistent with their function as major trade centers.

Los Angeles is also more specialized in retail, wholesale trade and transportation/warehousing sectors (NAICS sector 4), consistent with its role as the major international trade node in the US. As the state capital of California, Sacramento CSA has a uniquely high share of employment in public administration sector (NAICS sector 9). San Diego, on the other hand, has relatively higher percentage of employment in arts, entertainment and accommodation sectors (NAICS sector 7), reflecting its function as a major tourist destination. The different specialization in the four regions suggests a similar conclusion to the discussion above: LA and SF are relatively more specialized in manufacturing and trade while Sac and SD primarily provide local services and goods.

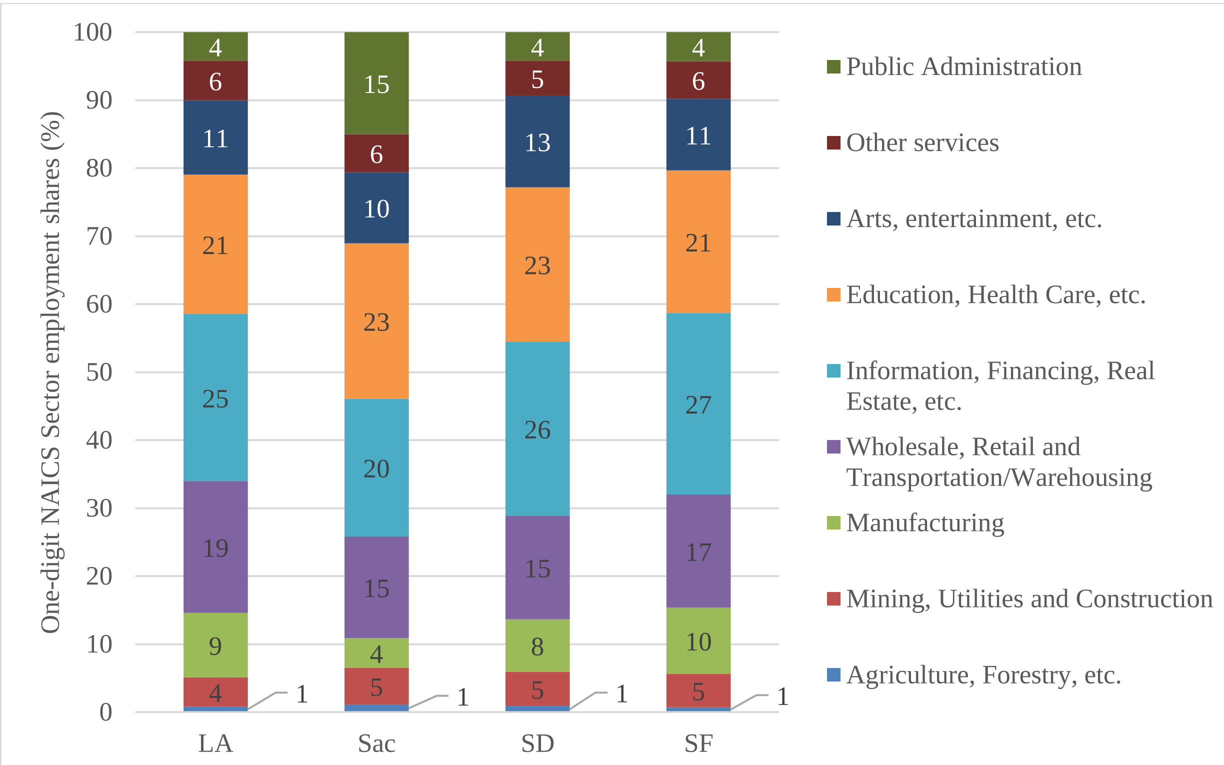


Figure 3. 23 One-digit NAICS Sector employment shares in the four regions

In summary, the four metropolitan areas are not only different in population and employment distribution, but also playing distinct roles in international and national trade. These regularities suggest a close relationship between freight intensity and socioeconomic characteristics. We will test the relationship using empirical data in the next chapter.

4 TESTING THE FREIGHT LANDSCAPE

In this chapter, we present Los Angeles and San Francisco case studies of the Freight Landscape analysis. The chapter begins with our general approach and model. We then describe the traffic flow data and present our results.

4.1 Research Approach

In Chapter 3 we presented the concept of freight landscape. We argue that freight activity should be related to development density. For all the reasons discussed, higher development density should lead to more intense freight demand, which in turn should results in more truck traffic on the urban network. Population and employment density may have different effects: areas with concentrated population but little employment may have a high level of general traffic, but lower truck traffic. Conversely, areas with concentrated employment but little population (e.g. industrial zones) may have lower general traffic but more truck traffic. Also, relative location should matter: areas with major links to the intercity system (e.g. major highway corridors) should experience more "through" traffic than more peripheral locations.

We estimate the intensity of truck activity as a function of land use characteristics. The general model is,

$$\mathrm{Y}_i = f(S_i, D_i) \qquad (1)$$

where Y = density measure of truck activity intensity in zone *i*, S = vector of transport supply and relative location measures, and D = vector of transport demand measures for zone *i*. We expect flow density to be related both to transport system supply and demand. In addition, we want to control for relative location – access to airports, seaports, or intermodal facilities – since, all else equal, we expect more truck traffic closer to such facilities.

We estimate two models. For Model 1 we use our development density categories, each reflective of a particular freight landscape. This model tests whether each given combination of population and employment density is significantly related to truck activity intensity. Model 1 assumes that population and employment are homogeneous. Since consumption is related to income and other household characteristics, it is possible that truck activity intensity varies with neighborhood characteristics. Similarly it is well known that some industry sectors are more freight intensive than others, for example warehousing compared to financial services. In Model 2 we consider the effects of population and employment characteristics. The model is

$$\mathrm{Y}_i = f(S_i, P_i, E_i) \qquad (2)$$

where Y and S are defined as in (1); P = vector of population characteristics; E = vector of employment characteristics. We discuss appropriate measures in the next section.

Our dependent variable is a measure of truck activity density in a zone. Thus we need some measure of truck flow. Ideally we would have actual data on truck traffic, but, as noted earlier, such data does not exist. We therefore use a second best approach. We obtained the equilibrium baseline traffic flow assignment from SCAG and MTC/ABAG respectively, and our dependent variable is calculated from the flows observed on each link within a given zone. MPOs use different transportation planning models with different levels of detail, vehicle classification, etc. If results are consistent across two very different metro areas using differently generated flow data, our hypothesis will have strong support. Before proceeding to development and testing of our models, we discuss the traffic flow data.

4.2 Introduction to the dataset and framework for travel model comparison in Los Angeles and San Francisco

In this case both transportation planning models are roughly consistent. Both are fairly sophisticated activity based models using agent-based simulation.

4.2.1 Basic statistics

For the Los Angeles metro, we use the SCAG RTP/SCS (Regional Transportation Plan / Sustainable Communities Strategy) 2008 baseline travel model. The SCAG model is based on 4,109 TAZs and it spans six counties (Los Angeles, Orange, San Bernardino, Riverside, Ventura, and Imperial). We exclude Imperial County (it is not part of the CSA). Table 4.1 gives the SCAG model network summary statistics. The model network is very large and detailed: it has 68,389 links, which amount to 41,423 km of link length and 111,599 km of link lanes. Highways account for approximately 17% of the total lane-km. The largest share of links are minor arterials, followed by principal arterials. Centroid connectors are virtual links that connect TAZs to the network, and they are not counted in the totals. The SCAG model transportation network covers 6.3 lane-km per one thousand residents, given its 17.6 million total population in 2010.

Table 4. 1 Summary statistics of SCAG RTP travel model

Facility type	Link N		Link length (km)		Lane-km (km)	
Freeway	7,000	10.2%	6,880.9	16.6%	18,944.6	17.0%
Expressway	215	0.3%	384.8	0.9%	770.3	0.7%
Principal arterial	14,922	21.8%	6,677.8	16.1%	25,341.7	22.7%
Minor arterial	22,130	32.4%	11,770.9	28.4%	34,202.1	30.6%
Major collector	9,788	14.3%	8,692.3	21.0%	19,810.6	17.8%
Minor collector	5,038	7.4%	4,032.6	9.7%	8,373.7	7.5%
Ramp	9,296	13.6%	2,983.6	7.2%	4,155.8	3.7%
Centroid connector	36,171	-	-	-	-	-
Sum (excludes cen. conn)	68,389	100.0%	41,422.8	100.0%	111,598.8	100.0%

For the San Francisco Bay Area, we use the 2013 RTP/SCS, model version 03, 2010 scenario, which reflects 2010 census results. The MTC model is based on 1,454 TAZs, and it spans 9 counties (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma). In Table 4.2, we present the MTC model summary statistics. The MTC model consists of 24,545 links, 19,068 km of link length and 31,604 link lane-km, excluding dummy links. Dummy links are equivalent to centroid connectors. Freeways account for approximately 23% of the total lane-km. Note that the facility types are different from that of the SCAG network. In general, the MTC network is less detailed than that of SCAG. The MTC model transportation network covers 4.6 lane-km per one thousand residents, given its 6.9 million total population in 2010. Maps 4.1 and 4.2 show the system and extent of SCAG and MTC transportation model networks, respectively. Note that the scale of the maps are different, because the LA metro area is much larger than SF.

Table 4. 2 Summary statistics of MTC RTP travel model

Facility type	Link N		Link length (km)		Lane-km (km)	
Freeway-to-freeway connector	231	0.9%	140.0	0.7%	226.7	0.7%
Freeway	2,765	11.3%	2,737.4	14.4%	7,142.6	22.6%
Expressway	862	3.5%	788.5	4.1%	1,541.7	4.9%
Major arterial	10,812	44.0%	7,618.0	40.0%	13,476.9	42.6%
Collector	7,772	31.7%	6,964.6	36.5%	8,310.2	26.3%
Freeway ramp	2,103	8.6%	819.6	4.3%	906.3	2.9%
Dummy link **	8,480	-	-	-	-	-
Sum (excluding **)	24,545	100.0%	19,068.2	100.0%	31,604.4	100.0%

**

4.2.2 Differences between models and data

There are many differences between the two models and the data generated. First, the size and geography of the two areas are quite different. Southern California as defined by SCAG, has a total area of 88,048 square km. This includes an urbanized area of 9,221 square km as defined by the 2010 census. San Francisco has a total of 18,246 square km, of which 3,855 square km is defined as urbanized. San Francisco is geographically more constrained: the Bay, the Pacific Ocean to the west and steep terrain to the east have both concentrated development around the bay and limited network connectivity. Los Angeles has been able to expand to the northwest and east, with a dense road network in the urbanized core.

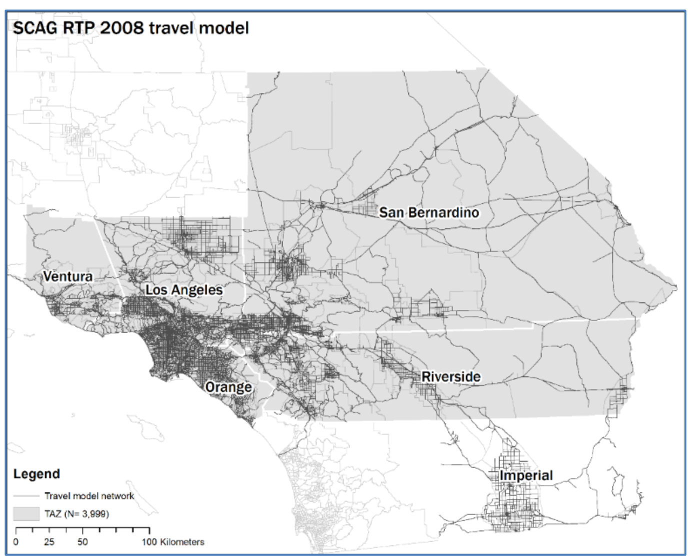


Figure 4. 1 SCAG RTP travel model

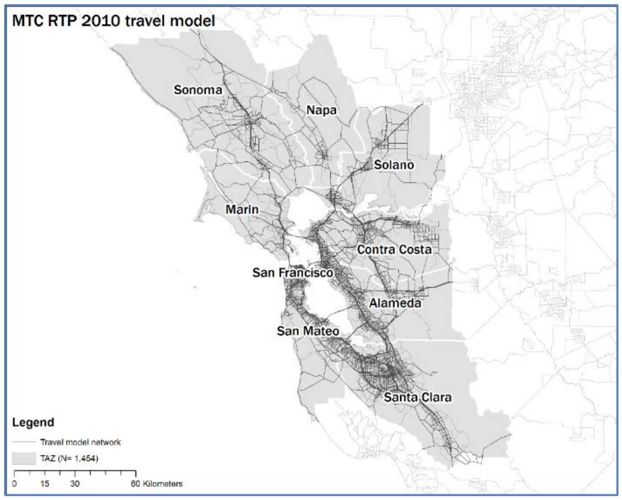


Figure 4. 2 MTC RTP travel model

Second, the network configurations are different. As noted above, facility types are different (Tables 4.1 and 4.2). We therefore aggregated them into 5 comparable groups, as shown in Figure 4.3, in units of link lane-km. The quantity of freeway lanes relative to population is quite comparable; Los Angeles has about 2.5 times the population and 2.6 times the freeway lane-km. However, the quantity of arterial lane-km relative to population is much higher for Los Angeles (about 4.4). This difference may in part be explained by the larger and more spread out pattern of urban development in Los Angeles.

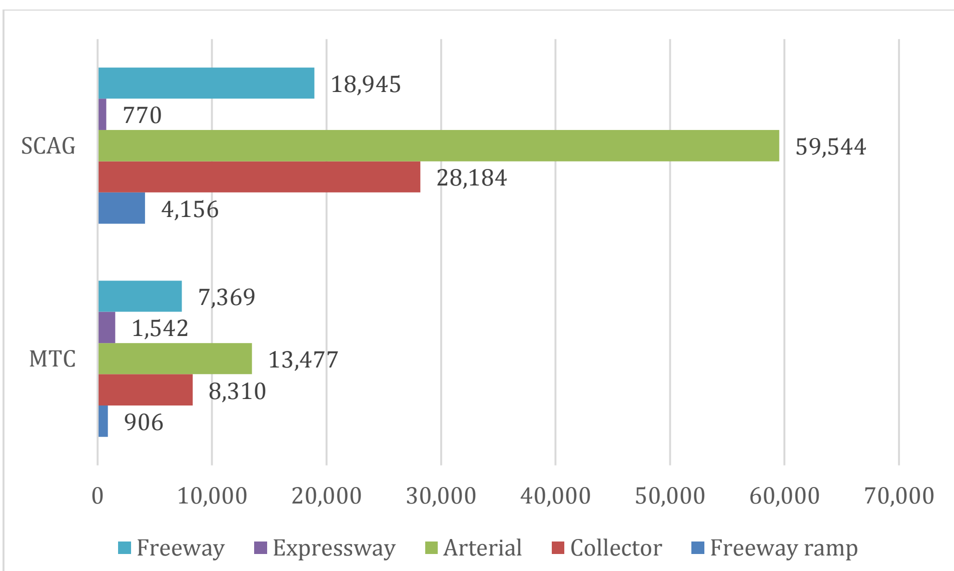


Figure 4. 3 Travel model transportation system comparison (lane-km)

Third, the network representation is different. Figure 4.4 illustrates. The two maps are in the same scale, and each show the downtown area, with Los Angeles on the left and San Francisco on the right. It can be seen that the SCAG model replicates the geometry of freeway networks, whereas the MTC model is a schematic representation.

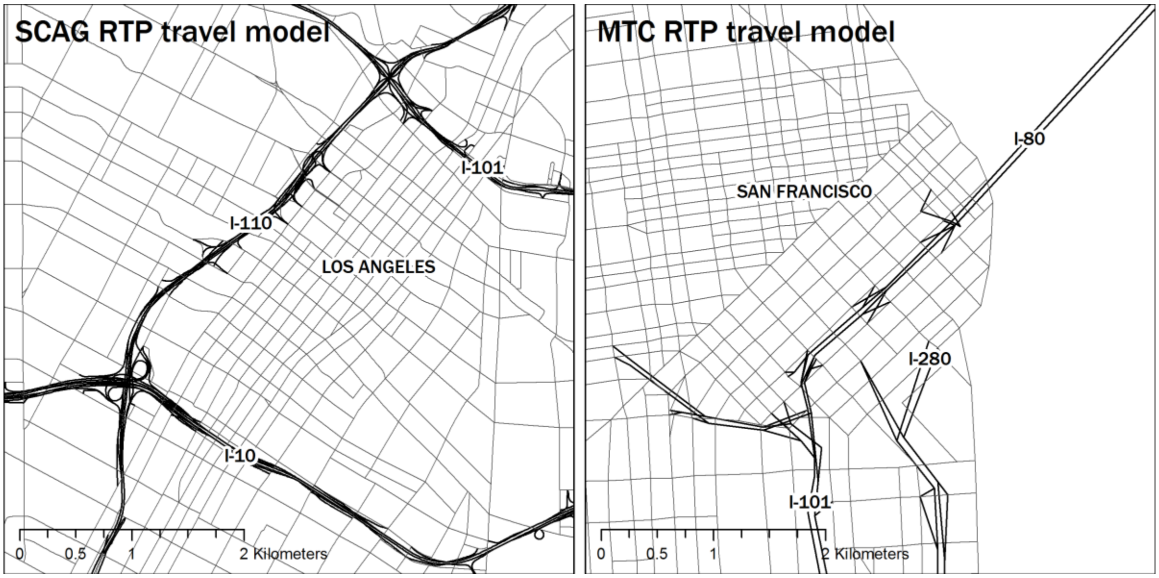


Figure 4. 4 Comparison of network representation

Lastly, the vehicle type classification differs between the two models. Transportation models classify vehicles both by type, and in the case of passenger vehicles, by occupancy. Our interest is in truck classification. The SCAG model classifies trucks based on weight, and the MTC model classifies based on number of axles. There is no precise way to translate between weight and axle count. Per the SCAG model, heavy-duty trucks are those with gross vehicle weight (GVW) of 8,500 lbs or more. Per the MTC model, large trucks have four or more axles; very small, small, and medium trucks have four-tire two axles, six-tire two axles, or three axles, respectively. MTC includes trucks with four-tire two axles in their commercial vehicle model, which includes trucks with GVW of less than 8,500 lbs. Given these differences, we expect systematic differences in the count of commercial vehicles between the two metropolitan areas.

4.3 Variables and Descriptive Statistics

In this section we discuss the variables to be used in our models.

4.3.1 Dependent variables

As noted in section 4.1, we want to measure freight flow intensity as our dependent variable. Thus, we need to construct some measure of the amount of flow that traverses each TAZ. We also want to compare our results on freight with total traffic. Network assignment for passenger travel is much more developed than assignment for trucks; total vehicles will provide a rough check on our estimations (see section 4.3.1.2 below for details). The discussion here applies both to trucks and total (passenger and truck) vehicles.

Constructing a measure of the amount of flow that traverses each TAZ is not straightforward, because network links do not start and end at TAZ borders. A network link may be located entirely within one TAZ, or may traverse several TAZs. Links are defined by their geometry and demand characteristics. We can assume that flow (volume) and performance (speed) are uniform across the link, because by definition vehicles may enter or exit a link only at a link node. Thus in order to generate a total flow for a TAZ, we take the volume of each link that traverses the TAZ, and generate vehicle km by multiplying volume and link length (e.g. the share of the link) within the TAZ. Because we want to measure intensity (rather than total quantity), we then divide by the area of the TAZ, thus generating a form of "traffic density" variable.

Because of the differences in the transportation models, we cannot expect to observe comparable levels of traffic density between the two metro areas. This is not a problem for our analysis. We are interested in testing the relationship between freight intensity and development density. Differences in the transportation model data may generate scale differences, but should not affect our estimation results. We do not expect coefficients to be the same, but rather of the same sign across models.

4.3.1.1 Freight flows in Los Angeles and San Francisco

To illustrate the spatial pattern of truck flows, Figure 4.5 shows truck VKT density in quartiles by TAZ within the Los Angeles Metropolitan Area. In general, truck activities are concentrated in the TAZs with major freeways, particularly those connecting major intermodal facilities or inter-regional destinations. The highest concentrations are found around the ports, the old industrial zone in the center of the region, in industrial zones around Ontario airport, and in the zones with the major inter-regional highways.

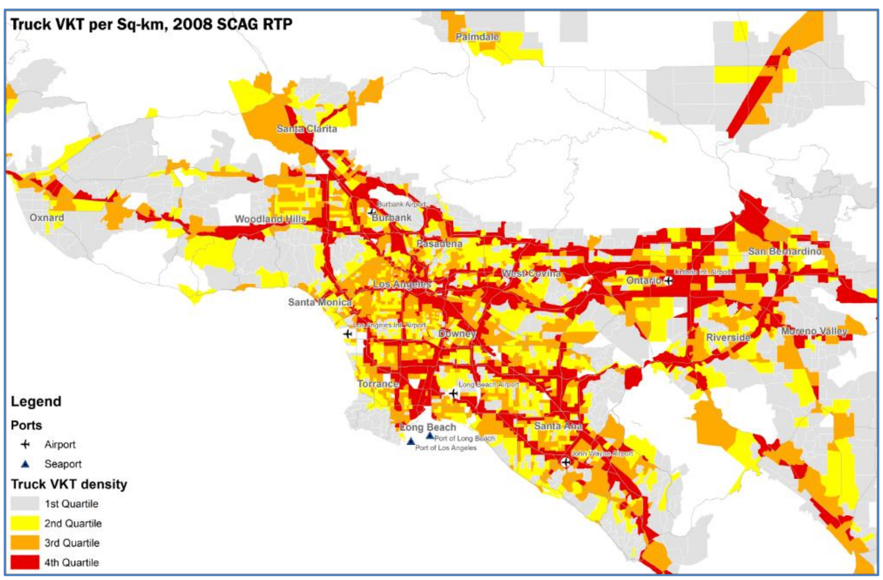


Figure 4. 5 Truck VKT density in TAZs in quartiles within the Los Angeles Metropolitan Area

Figure 4.6 shows the same data for the San Francisco Metropolitan Area. Similar to Los Angeles, truck activities are concentrated along the main highway corridors on either side of the bay, around the downtown cores, and around the major airports. With high employment density, the zones around the San Jose Airport appear to be a truck density hotspot. The spatial distribution of truck activities in San Francisco is far less spread out than Los Angeles, again reflecting the geographic constraints of this metro area.

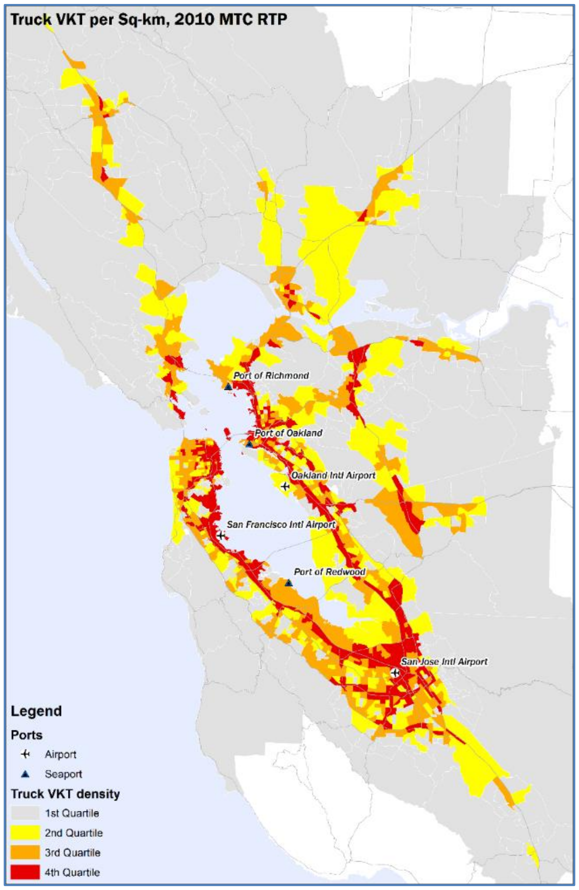


Figure 4. 6 Truck VKT density in TAZs in quartiles within the San Francisco Metropolitan Area

4.3.1.2 Descriptive Statistics

Descriptive statistics for dependent variables are given in Table 4.3. The mean for total traffic density (total vehicle VKT/km2) is high in both metro areas, but notably higher for Los Angeles. The distribution is skewed, with the median much lower than the mean in both cases and for both dependent variables. Truck traffic density is greater and a larger percentage of total traffic density for San Francisco (10% for San Francisco, 5% for Los Angeles). This is likely due to differences in how trucks are defined.

Table 4. 3 VKT density variables descriptive statistics for Los Angeles and San Francisco

Variable	Mean	Median	S.D.	Min	Max
Los Angeles (N = 3736)					
Total truck VKT per sq-km	4,432	1,198	7,578	0	90,544
Total vehicle VKT per sq-km	91,512	50,850	116,260	20	952,379
San Francisco (N = 1392)					
Total truck VKT per sq-km	6,889	3,060	10,422	0	119,589
Total vehicle VKT per sq-km	68,186	41,315	76,137	0	641,264

4.3.2 Independent Variables

As presented in Section 4.1, we estimate two model forms. Model 1 estimates traffic density as a function of transportation access and network characteristics, and of our development density measure. Model 2 replaces the development density measure with population and employment characteristics.

4.3.2.1 Access Measures

Proximity to freight generators -- airports, seaports and intermodal facilities -- should affect the freight intensity of a TAZ. These major facilities are connected to the freeway network; TAZs along these corridors likely receive substantial through traffic. Proximity can be measured in many ways. The simplest is Euclidean distance, but Euclidean distance does not take into account possible differences in network accessibility. This could be a problem in San Francisco, where the links across the bay are limited. We therefore calculated both Euclidean distance and network distance to the nearest airport, seaport, and intermodal facility. As expected, the two measures are different; network distance is always greater than Euclidean distance, but the difference is very consistent. For Los Angeles, the correlations are 0.97 for distance to the nearest airport, 0.98 for nearest seaport, and 0.97 for nearest intermodal facility. For San Francisco, the same correlations are 0.99, 0.98 and 0.97 respectively. We also compared the distributions of the variables and found no statistical differences. We therefore use Euclidean distance in our model estimations. Descriptive statistics are given in Table 4.4.

Table 4. 4 Descriptive statistics for distance measures, Los Angeles and San Francisco

Variable	Mean	Median	S.D.	Min	Max
Los Angeles (N = 3736)					
Euclidean Distance to nearest airport (km)	24.8	16.9	24.8	0.3	283.9
Network Distance to nearest airport (km)	31.7	21.4	31.3	0.4	324.4
Euclidean Distance to nearest seaport (km)	54.1	43.1	35.6	1.2	336.5
Network Distance to nearest seaport (km)	67.3	50.5	48.3	1.7	402.7
Euclidean Distance to nearest intermodal (km)	26.4	18.5	24.2	0.4	258.4
Network Distance to nearest intermodal (km)	34.5	24.5	31.4	0.4	299.8
San Francisco (N = 1392)					
Euclidean Distance to nearest airport (km)	23.1	16.4	20.6	0.1	114.2
Network Distance to nearest airport (km)	27.8	19.3	24.3	0.2	127.9
Euclidean Distance to nearest seaport (km)	37.1	33.1	23.6	0.1	112.7
Network Distance to nearest seaport (km)	44.0	41.3	26.0	0.2	119.3
Euclidean Distance to nearest intermodal (km)	36.5	32.3	23.2	0.6	110.8
Network Distance to nearest intermodal (km)	43.0	40.2	25.6	0.7	116.6

There is another concern about the access variables in San Francisco. As we have mentioned in Section 3.4.1, in SF region there is one major seaport, the Port of Oakland, and one intermodal facility which is located near the port and jointly operated by BNSF and UP. The spatial proximity between the only seaport and intermodal facility leads to a multicollinearity problem between distance to seaports and distance to intermodal facilities. We thus drop the latter in the SF models and treat the former as distance to seaport and intermodal facility.

4.3.2.2 Population and Employment Measures

For Model 1 we use our 16 category development density measure that was discussed in Chapter 3. In our models we use dummy variables, with the lowest density category, P1/E1, as the omitted category. In Model 2 we hypothesize that population and employment characteristics may affect freight intensity. We use median household income as a measure of consumption demand, and population density as a measure of consumer demand concentration. We explored different measures for employment. We conducted a factor analysis on the 2 digit NAICS LEHD employment data, and then clustered TAZ employment by the resulting factors. It should be noted that we are doing a spatial factor analysis, and the factors reflect which sectors may co-locate.

For the Los Angeles case, the factor analysis generated four factors with five industry sectors (agriculture, mining, utility, information and education) left out. Since agriculture, mining and utility employments accounts for just 1.9% of total employment, we combined them and treated them as one omitted sector. Information (5.5% of total employment) and education (10.0% of total employment) sectors are treated individually. Based on the factor analysis, we aggregate employment into seven aggregated industry sectors and calculate density measures. The aggregated sector designation is as follows:

Sector 1: finance, real estate, professional, management, administrative & accommodation
Sector 2: construction, transportation, arts & public
Sector 3: manufacturing, wholesale & retail trade
Sector 4: health & other
Sector 5: agriculture, mining & utility
Sector 6: information
Sector 7: education

For the San Francisco case, the factor analysis generated two factors with two industry sectors (manufacturing and education) left out. The manufacturing and education sectors are treated separately. Based on the factor analysis, we aggregate employment into four industry sectors and calculate density measures. The aggregated sector designation is as follows:

Sector 1: agriculture, mining, construction, wholesale trade, retail trade, information, finance, real estate, professional, management, administration, accommodation and others.
Sector 2: utility, transportation, health, arts and public.
Sector 3: manufacturing
Sector 4: education

The first sector includes disparate industry sectors that are not expected to co-locate, because of differences in land intensity and value of local agglomeration economies. We surmise that this is an artifact of the general geographic concentration of employment along the freeway corridors surrounding the bay.

We also used simpler measures of employment: employment density, and relative diversity. The relative diversity index is defined as the inverse of the sum of the absolute difference of industry j's share in location i (S_{ij}) from the regional employment share of industry j. A higher diversity index represents more similar industry composition of location i to the industry composition of the entire region (Duranton, G. and Puga, D., 2000, Equation (3)).

$$RDI_i = 1/\sum_j |s_{ij} - s_j| \tag{3}$$

In Model 2, we test whether more detailed measures of employment and population are more effective in explaining traffic activity. We estimate two forms of the model. Model 2a uses total employment density and relative diversity; Model 2b uses the factor analysis generated industry sectors.
Descriptive statistics for the population and second set of employment variables are given in Table 4.5

Table 4. 5 Descriptive statistics for population and employment measures, Los Angeles and San Francisco

Variable	Mean	Median	S.D.	Min	Max
Los Angeles (N = 3736)					
Population Density	3,622	2,826	3,455	1	35,021
Median HH Income	64,988	59,463	30,058	2,500	231,649
Employment Density	15,65	562	6,921	1	247,630
Relative Diversity	1.0	1.0	0.2	0.5	2.3
San Francisco (N = 1392)					
Population Density	3,857	2,873	4,093	13	44,682
Median HH Income	82,382	77,444	35,504	6,124	25,0001
Employment Density	2,427	555	9,836	7	127,416
Relative Diversity	1.1	1.1	0.3	0.6	2.7

4.4 Results

We turn now to model results. Due to the shape of the variable distributions, we use the natural log form for all dependent and independent variables except the categorical variables (density dummies) and the relative diversity variable. For each model we estimate two regressions, one for total vehicle volume density, and one for truck volume density. Total vehicle volume density provides a means for comparing the extent to which truck volume patterns are different from the general pattern of vehicle traffic.

We hypothesize that access to major trip generators, whether passenger or freight, is associated with greater volume density. We have no *a priori* expectations for the relationship between total traffic and distance to seaports and intermodal. These large facilities generate substantial externalities and may repel passenger traffic, or as part of major industrial zones may attract passenger traffic. Access to highways should have a positive effect: we expect more development density (and hence more travel demand) in more accessible locations. However, the roles of population and employment density should differ between truck and total vehicle volume, as discussed in Section 3.2.

Another consideration in model estimation is spatial autocorrelation. Zones in close proximity to one another have similar accessibility characteristics, and traffic volume in one zone must be correlated with that of nearby zones. We therefore estimated simple regressions for each model and tested for spatial autocorrelation using the Moran's I measure. All tests were significant (results not shown). We therefore estimate spatial lag models (see Boarnet, 1994; Wouldsma et al, 2008). We create Queen Contiguity Weights matrices for the dependent variables and calculate the spatially lagged terms based on the matrices.

4.4.1 Model 1

4.4.1.1 Los Angeles Case

Results for Model 1 are given in Tables 4.6 and 4.7 for total vehicles and trucks respectively. We present stepwise results, with just the control variables in the first step, and with all variables in the second step. The spatial lag term coefficient is significant and positive, as expected. For total vehicles VKT (Table 4.6), all control variable coefficients have the expected sign, with all but distance to airport statistically significant. Results are more mixed for total truck VKT (Table 4.7): the coefficient for distance to highway is significant and of the expected sign, coefficients for the other access measures are not. For highway access, the magnitude of the coefficient is substantially greater for trucks than for all vehicles, as would be expected (total vehicle traffic should be more dispersed, and large trucks must observe route restrictions).

When we add the development density dummy variables, the explanatory power of both estimations increases, but not by much. The magnitude of some of the access variable coefficients goes down for total vehicles, but not for trucks. All coefficients are relative to the base, P1/E1. For the total vehicles regression, all of the coefficients are significant and positive, as expected. We observe a general relationship: for each population category: the coefficient value tends to increase with increasing employment density. Also, the P4/E4 category has the largest coefficient.

Relationships for total truck VKT are similar but more complex. Eleven of the 15 coefficients are statistically significant and have the expected positive signs. Similar to the total vehicle model, for each population category, the coefficient value tends to increase with increasing employment density. But for each employment category, the coefficient value generally decreases with increasing population density, which does not occur in the total vehicle model. The results may imply that the intensity of freight activities is influenced by both employment and population density, but in opposite directions. Finally, both models have a reasonable level of explanatory power.

Table 4. 6 Model 1 results, Los Angeles, total vehicles

Dependent variable: VKT/KM2, Total Vehicles						
	Step 1			Step 2		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.394	(0.019)	***	0.290	(0.019)	***
Distance to Hwy	-0.560	(0.018)	***	-0.515	(0.017)	***
Distance to Airport	-0.062	(0.024)	***	-0.010	(0.023)	
Distance to Seaports	-0.131	(0.032)	***	-0.069	(0.031)	***
Distance to Intermodal	-0.067	(0.020)	***	-0.040	(0.020)	***
Pop Q1 Emp Q2				0.669	(0.084)	***
Pop Q1 Emp Q3				0.820	(0.094)	***
Pop Q1 Emp Q4				0.994	(0.080)	***
Pop Q2 Emp Q1				0.322	(0.067)	***
Pop Q2 Emp Q2				0.744	(0.062)	***
Pop Q2 Emp Q3				0.927	(0.071)	***
Pop Q2 Emp Q4				0.931	(0.072)	***
Pop Q3 Emp Q1				0.540	(0.089)	***
Pop Q3 Emp Q2				0.856	(0.065)	***
Pop Q3 Emp Q3				0.833	(0.064)	***
Pop Q3 Emp Q4				1.018	(0.074)	***
Pop Q4 Emp Q1				0.697	(0.121)	***
Pop Q4 Emp Q2				0.656	(0.074)	***
Pop Q4 Emp Q3				0.869	(0.067)	***
Pop Q4 Emp Q4				1.036	(0.066)	***
Constant	7.513	(0.254)	***	7.432	(0.254)	***
Pseudo R-squared	0.562			0.598		
Sample Size	3774			3774		

Table 4. 7 Model 1 results, Los Angeles, total trucks

Dependent variable: VKT/KM2, Total Trucks						
	Step 1			Step 2		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.400	(0.019)	***	0.375	(0.019)	***
Distance to Hwy	-0.810	(0.024)	***	-0.764	(0.025)	***
Distance to Airport	-0.008	(0.032)		0.025	(0.032)	
Distance to Seaports	-0.043	(0.043)		-0.031	(0.043)	
Distance to Intermodal	-0.031	(0.027)		-0.036	(0.027)	
Pop Q1 Emp Q2				0.688	(0.117)	***
Pop Q1 Emp Q3				0.786	(0.131)	***
Pop Q1 Emp Q4				0.791	(0.110)	***
Pop Q2 Emp Q1				-0.122	(0.094)	
Pop Q2 Emp Q2				0.427	(0.086)	***
Pop Q2 Emp Q3				0.639	(0.099)	***
Pop Q2 Emp Q4				0.508	(0.099)	***
Pop Q3 Emp Q1				-0.015	(0.124)	
Pop Q3 Emp Q2				0.453	(0.089)	***
Pop Q3 Emp Q3				0.305	(0.088)	***
Pop Q3 Emp Q4				0.532	(0.102)	***
Pop Q4 Emp Q1				-0.029	(0.168)	
Pop Q4 Emp Q2				0.064	(0.102)	
Pop Q4 Emp Q3				0.276	(0.092)	***
Pop Q4 Emp Q4				0.378	(0.090)	***
Constant	2.795	(0.186)	***	4.499	(0.221)	***
Pseudo R-squared	0.525			0.544		
Sample Size	3774			3774		

4.4.1.2 San Francisco Case

Despite the smaller number of observations and differences in the traffic flow data, the results of Model 1 for San Francisco are quite similar to those for Los Angeles. Coefficients for the spatial lagged term and distance to highway variables are both highly significant. Distance to airports and distance to seaports do not have the same negative effects on total vehicle truck VKT densities as in the Los Angeles case. The reasons for the distinctions are unknown; one possible factor is the geography: airports and seaports are located in the same places as major employment and population clusters.

The magnitudes of the coefficients for the development density variables are all statistically significant and slightly larger in SF, compared to LA. More importantly, the same pattern is observed: as employment density increases, for any given level of population density, so does total traffic and, to a lesser extent truck traffic. We do not observe decreases in coefficient magnitudes with increasing population density for each employment category. Population densities do not have a robust effect on truck activities, if we control the influences of employment densities. Both models have reasonable overall fit, given the smaller number of observations.

Table 4. 8 Model 1 results, San Francisco, total vehicles

Dependent variable: VKT/KM2, Total Vehicles						
	Step 1			Step 2		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.446	(0.028)	***	0.359	(0.028)	***
Distance to Hwy	-0.574	(0.031)	***	-0.476	(0.030)	***
Distance to Airports	-0.030	(0.036)		0.066	(0.036)	*
Distance to Seaports	-0.017	(0.034)		0.081	(0.036)	**
Pop Q1 Emp Q2				0.860	(0.140)	***
Pop Q1 Emp Q3				1.184	(0.161)	***
Pop Q1 Emp Q4				1.299	(0.158)	***
Pop Q2 Emp Q1				0.762	(0.120)	***
Pop Q2 Emp Q2				1.003	(0.120)	***
Pop Q2 Emp Q3				1.043	(0.126)	***
Pop Q2 Emp Q4				1.369	(0.132)	***
Pop Q3 Emp Q1				0.759	(0.150)	***
Pop Q3 Emp Q2				1.075	(0.116)	***
Pop Q3 Emp Q3				1.096	(0.120)	***
Pop Q3 Emp Q4				1.358	(0.138)	***
Pop Q4 Emp Q1				0.903	(0.320)	***
Pop Q4 Emp Q2				1.001	(0.132)	***
Pop Q4 Emp Q3				1.129	(0.120)	***
Pop Q4 Emp Q4				1.567	(0.119)	***
Constant	6.002	(0.352)	***	5.330	(0.347)	***
Pseudo R-squared	0.465			0.536		
Sample Size	1396			1396		

Table 4. 9 Model 1 results, San Francisco, total trucks

Dependent variable: VKT/KM2, Total Trucks						
	Step 1			Step 2		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.559	(0.025)	***	0.480	(0.026)	***
Distance to Hwy	-0.612	(0.033)	***	-0.525	(0.032)	***
Distance to Airports	0.022	(0.037)		0.098	(0.038)	**
Distance to Seaports	-0.050	(0.036)		0.024	(0.039)	
Pop Q1 Emp Q2				0.861	(0.151)	***
Pop Q1 Emp Q3				1.249	(0.173)	***
Pop Q1 Emp Q4				1.404	(0.170)	***
Pop Q2 Emp Q1				0.615	(0.129)	***
Pop Q2 Emp Q2				0.843	(0.128)	***
Pop Q2 Emp Q3				0.922	(0.135)	***
Pop Q2 Emp Q4				1.323	(0.141)	***
Pop Q3 Emp Q1				0.569	(0.161)	***
Pop Q3 Emp Q2				0.893	(0.124)	***
Pop Q3 Emp Q3				0.894	(0.128)	***
Pop Q3 Emp Q4				1.240	(0.148)	***
Pop Q4 Emp Q1				0.619	(0.343)	*
Pop Q4 Emp Q2				0.637	(0.141)	***
Pop Q4 Emp Q3				0.852	(0.128)	***
Pop Q4 Emp Q4				1.460	(0.128)	***
Constant	3.641	(0.276)	***	2.956	(0.289)	***
Pseudo R-squared	0.539			0.589		
Sample Size	1396			1396		

4.4.2 Model 2

Results for Models 2a and 2b are presented in this section

4.4.2.1 Los Angeles Case

Results for Model 2a are given in Tables 4.10 and 4.11, again for total vehicles and trucks respectively. We present stepwise results; step 1 includes the spatial lag and control variables, step 2 adds the population variables, and step 3 adds the employment variables. As with Model 1, the step 1 coefficient of access to highway is significant and of the expected sign, but the distance to other freight generators coefficients are not statistically significant in the truck model. When we add population characteristics in step 2, both median income and population density coefficients are significant. Signs are as expected – traffic activity is higher in high-density areas, and higher income households typically locate further from major traffic generators. For truck volume, both coefficients are significant and negative as expected.

Results change with step 3. Both employment variable coefficients are significant, and as in Model 1, explanatory value also increases. This suggests that employment characteristics do a better job of explaining total vehicle traffic than population characteristics. In contrast, for truck volume, adding the employment variables does not affect the coefficients of the other variables. Both are significant and have the expected sign.

Table 4. 10 Model 2 results, Los Angeles, total vehicles

	Dependent variable: VKT/KM2, Total Vehicles (Using total employment density and diversity)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig	Coef.	S.E	Sig	Coef.	S.E	Sig.
Spatial lagged term	0.397	(0.019)	***	0.374	(0.019)	***	0.277	(0.019)	***
Distance to Hwy	-0.558	(0.017)	***	-0.549	(0.017)	***	-0.511	(0.017)	***
Distance to Airport	-0.066	(0.024)	***	-0.080	(0.024)	***	-0.029	(0.023)	
Distance to Seaports	-0.136	(0.032)	***	-0.137	(0.033)	***	-0.098	(0.031)	***
Distance to Intermodal	-0.066	(0.020)	***	-0.015	(0.021)		-0.033	(0.020)	*
Population Density				0.055	(0.011)	***	0.031	(0.010)	***
Median HH Income				-0.184	(0.034)	***	-0.075	(0.034)	**
Employment Density							0.201	(0.011)	***
Relative Diversity							0.172	(0.056)	**
Constant	7.519	(0.254)	***	9.267	(0.504)	***	7.619	(0.494)	***
Pseudo R-squared	0.569			0.576			0.608		
Sample Size	3736			3736			3736		

Table 4. 11 Model 2 results, Los Angeles, total trucks

	Dependent variable: VKT/KM2, Total Trucks (Using total employment density and diversity)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig	Coef.	S.E	Sig	Coef.	S.E	Sig.
Spatial lagged term	0.405	(0.019)	***	0.390	(0.019)	***	0.360	(0.019)	***
Distance to Hwy	-0.805	(0.024)	***	-0.809	(0.024)	***	-0.767	(0.024)	***
Distance to Airport	-0.020	(0.032)		-0.051	(0.032)		-0.001	(0.032)	
Distance to Seaports	-0.027	(0.043)		-0.098	(0.044)	**	-0.058	(0.044)	
Distance to Intermodal	-0.034	(0.027)		0.000	(0.028)		-0.013	(0.028)	
Population Density				-0.080	(0.015)	***	-0.109	(0.015)	***
Median HH Income				-0.272	(0.047)	***	-0.212	(0.048)	***
Employment Density							0.145	(0.016)	***
Relative Diversity							0.362	(0.078)	***
Constant	4.730	(0.197)	***	8.693	(0.619)	***	6.925	(0.641)	***
Pseudo R-squared	0.530			0.535			0.549		
Sample Size	3736			3736			3736		

Results for Model 2b are given in Tables 4.12 and 4.13. The Step 1 and 2 estimations are the same as Model 2a, as the only difference between the two models is how we measure employment activity. We observe the same result for total vehicle VKT density (Table 13a) as for Model 2a; the coefficient for population density loses significance. In this case five of the seven sector variable coefficients and the diversity variable coefficient are significant. For truck VKT density, results are also similar to those of Model 2a; when employment variables are added, the population and control variable coefficients are not affected. Just three of the employment variables coefficients are significant, though the two that should have the greatest effect on truck traffic (services; manufacturing and trade) are positive and significant, as expected. How to interpret the results of the sector variables is unclear.

We examined the employment sector data to try to understand why the more sector specific measures did not perform as well as the simple employment measures. First, the sector level measures are correlated with each other (correlations range from .5 to .7). As noted earlier, employment is more concentrated than population. Although clearly employment mix varies spatially, the spatial variation of these large aggregations of sectors tends toward the spatial variation of total employment. Second, the effects of some industries (say transportation) may be captured by the access variables which are the main generators of such traffic.

Both versions of Model 2 are generally consistent. The access measure coefficients have the expected sign, though in several cases are not significant. Population and employment measures are generally consistent across the models, and differences between total vehicles and trucks are as expected.

Table 4. 12 Model 2 results, Los Angeles, total vehicles

	Dependent variable: VKT/KM2, Total Vehicles (Using seven industry sector employment densities and diversity)								
	Step 1			Step 2			Step 3		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.397	(0.019)	***	0.374	(0.019)	***	0.282	(0.019)	***
Distance to Hwy	-0.558	(0.017)	***	-0.549	(0.017)	***	-0.511	(0.017)	***
Distance to Airport	-0.066	(0.024)	***	-0.080	(0.024)	***	-0.033	(0.023)	
Distance to Seaports	-0.136	(0.032)	***	-0.137	(0.033)	***	-0.080	(0.032)	***
Distance to Intermodal	-0.066	(0.020)	***	-0.015	(0.021)		-0.039	(0.020)	*
Population Density				0.055	(0.011)	***	0.018	(0.012)	
Median HH Income				-0.184	(0.034)	***	-0.087	(0.034)	**
Emp S1 (services)							0.113	(0.015)	***
Emp S2 (const, transp)							-0.005	(0.013)	
Emp S3 (manuf, trade)							0.070	(0.012)	***
Emp S4 (health, other)							0.043	(0.015)	***
Emp S5 (agri, util)							-0.017	(0.013)	
Emp S6 (info)							-0.028	(0.012)	**
Emp S7 (educ)							0.015	(0.007)	**
Constant	7.519	(0.254)	***	9.267	(0.504)	***	8.181	(0.496)	***
Pseudo R-squared	0.569			0.576			0.613		
Sample Size	3736			3736			3736		

Table 4. 13 Model 2 results, Los Angeles, total trucks

	Dependent variable: VKT/KM2, Total Trucks (Using seven industry sector employment densities and diversity)								
	Step 1			Step 2			Step 3		
	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.	Coefficient	S.E	Sig.
Spatial lagged term	0.405	(0.019)	***	0.390	(0.019)	***	0.349	(0.019)	***
Distance to Hwy	-0.805	(0.024)	***	-0.809	(0.024)	***	-0.769	(0.024)	***
Distance to Airport	-0.020	(0.032)		-0.051	(0.032)		-0.005	(0.032)	
Distance to Seaports	-0.027	(0.043)		-0.098	(0.044)	**	-0.027	(0.044)	
Distance to Intermodal	-0.034	(0.027)		0.000	(0.028)		-0.024	(0.028)	
Population Density				-0.080	(0.015)	***	-0.081	(0.017)	***
Median HH Income				-0.272	(0.047)	***	-0.207	(0.048)	***
Emp S1 (services)							0.109	(0.021)	***
Emp S2 (const, transp)							0.005	(0.018)	
Emp S3 (manuf, trade)							0.123	(0.016)	***
Emp S4 (health, other)							-0.072	(0.021)	***
Emp S5 (agri, util)							-0.025	(0.018)	
Emp S6 (info)							-0.027	(0.016)	
Emp S7 (educ)							0.012	(0.010)	
Constant	4.730	(0.197)	***	8.693	(0.619)	***	7.240	(0.639)	***
Pseudo R-squared	0.530			0.535			0.557		
Sample Size	3736			3736			3736		

4.4.2.2 San Francisco Case

Results in the San Francisco case are not very different from the LA case (Tables 4.14 and 4.15). For Model 2a, apart from the aforementioned differences in the coefficients of the access variables, population characteristics do not play as strong a role as in Los Angeles. For both total vehicles and total trucks, the coefficients for median household income are no longer statistically significant when we add employment variables. Thus suggests that in San Francisco, population characteristics may have a weaker effect on truck activities than employment characteristics. This finding is consistent with what we found in the Model 1. However, we have not obtained enough evidence showing why population characteristics function differently in these two metropolitan areas.

Table 4. 14 Model 2 results, San Francisco, total vehicles

	Dependent variable: VKT/KM2, Total Vehicles (Using total employment density and diversity)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig	Coef.	S.E	Sig	Coef.	S.E	Sig.
Spatial lagged term	0.446	(0.028)	***	0.400	(0.026)	***	0.323	(0.028)	***
Distance to Hwy	-0.573	(0.031)	***	-0.535	(0.033)	***	-0.490	(0.029)	***
Distance to Airport	-0.028	(0.036)		0.001	(0.038)		0.018	(0.035)	
Distance to Seaports	-0.016	(0.034)		0.087	(0.038)	**	0.134	(0.034)	***
Population Density				0.223	(0.030)	***	0.122	(0.028)	***
Median HH Income				-0.139	(0.068)	**	-0.024	(0.061)	
Employment Density							0.253	(0.022)	***
Relative Diversity							0.301	(0.087)	***
Constant	5.991	(0.352)	***	8.252	(0.920)	***	4.011	(0.846)	***
Pseudo R-squared	0.463			0.490			0.536		
Sample Size	1392			1392			1392		

Table 4. 15 Model 2 results, San Francisco, total trucks

	Dependent variable: VKT/KM2, Total Trucks (Using total employment density and diversity)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig	Coef.	S.E	Sig	Coef.	S.E	Sig.
Spatial lagged term	0.559	(0.025)	***	0.540	(0.026)	***	0.430	(0.027)	***
Distance to Hwy	-0.612	(0.033)	***	-0.581	(0.033)	***	-0.539	(0.031)	***
Distance to Airport	0.023	(0.038)		0.042	(0.038)		0.062	(0.037)	*
Distance to Seaports	-0.050	(0.036)		0.021	(0.038)		0.063	(0.036)	*
Population Density				0.143	(0.030)	***	0.017	(0.030)	
Median HH Income				-0.126	(0.068)	*	0.015	(0.065)	
Employment Density							0.311	(0.024)	***
Relative Diversity							0.342	(0.093)	***
Constant	3.638	(0.276)	***	3.792	(0.920)	***	1.508	(0.880)	*
Pseudo R-squared	0.538			0.547			0.592		
Sample Size	1392			1392			1392		

For model 2b, the San Francisco case is more difficult to interpret. Given that the Sector 1 includes the majority of the industry sectors, it has much stronger effects on VKT densities than the other three sector variables. Unlike the Los Angeles case, the population variable coefficients decline in magnitude and significance when we add employment sector variables to the total truck regression. All of the three sector variables have significant coefficients in both models, as expected. Overall, the inclusion of sector employment variables substantially contributes to the increase in the R-squared for the two models.

Table 4. 16 Model 2 results, San Francisco, total vehicles

	Dependent variable: VKT/KM2, Total Vehicles (Using four industry sector total employment densities)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig.	Coef.	S.E	Sig.	Coef.	S.E	Sig.
Spatial lagged term	0.446	(0.028)	***	0.400	(0.026)	***	0.318	(0.028)	***
Distance to Hwy	-0.573	(0.031)	***	-0.535	(0.033)	***	-0.491	(0.029)	***
Distance to Airport	-0.028	(0.036)		0.001	(0.038)		0.024	(0.034)	
Distance to Seaports	-0.016	(0.034)		0.087	(0.038)	**	0.139	(0.034)	***
Population Density				0.223	(0.030)	***	0.076	(0.031)	**
Median HH Income				-0.139	(0.068)	**	-0.001	(0.061)	
Emp S1 (const, trade, info, etc.)							0.268	(0.034)	***
Emp S2 (util, transp, etc.)							0.022	(0.024)	
Emp S3 (manuf)							-0.021	(0.017)	
Emp S4 (educ)							0.016	(0.017)	
Constant	5.991	(0.352)	***	8.252	(0.920)	***	4.423	(0.849)	***
Pseudo R-squared	0.463			0.490			0.540		
Sample Size	1392			1392			1392		

Table 4. 17 Model 2 results, San Francisco, total trucks

	Dependent variable: VKT/KM2, Total Vehicles (Using four industry sector total employment densities)								
	Step 1			Step 2			Step 3		
	Coef.	S.E	Sig.	Coef.	S.E	Sig.	Coef.	S.E	Sig.
Spatial lagged term	0.559	(0.025)	***	0.540	(0.026)	***	0.421	(0.027)	***
Distance to Hwy	-0.612	(0.033)	***	-0.581	(0.033)	***	-0.540	(0.031)	***
Distance to Airport	0.023	(0.038)		0.042	(0.038)		0.075	(0.037)	**
Distance to Seaports	-0.050	(0.036)		0.021	(0.038)		0.066	(0.036)	*
Population Density				0.143	(0.03)	***	-0.022	(0.033)	
Median HH Income				-0.126	(0.068)	*	0.049	(0.065)	
Emp S1 (const, trade, info, etc.)							0.315	(0.037)	***
Emp S2 (util, transp, etc.)							0.023	(0.026)	
Emp S3 (manuf)							-0.004	(0.019)	
Emp S4 (educ)							0.015	(0.018)	
Constant	3.638	(0.276)	***	3.792	(0.92)	***	1.844	(0.883)	**
Pseudo R-squared	0.538			0.547			0.596		
Sample Size	1392			1392			1392		

4.5 Summary

Although Los Angeles and San Francisco are different in many ways, the models generate highly consistent results. In most cases, we find that transport supply and highway access are significant factors, with the effects of greater magnitude for trucks than for total vehicles. Access to major generators (airports, seaports, intermodal facilities) is generally significant for total vehicles, but not for trucks, suggesting that even in a hub region like Los Angeles and San Francisco, truck traffic is related more to general economic activity. The way in which access to major generators affects total vehicles and trucks VKT densities is different, probably due to the unique geographical constraints in the Bay Area. Using the simple categories of combined population and employment in Model 1, results for total vehicles are consistent and as expected: traffic increases systematically with increasing population and employment density. However, results for truck activities are mixed. There is a generally systematic relationship with density, but it is more complicated. For each population category, the coefficient value tends to increase with increasing employment density. But for each employment category, the coefficient value generally decreases with increasing population density.

In Model 2 we separate the effects of population and employment. Using employment density and relative diversity, there is a clear positive relationship of total vehicles with employment density. The relationship for truck volume is as expected, negative for population density and positive for employment density. When we replace a single employment density measure with sector level measures, not all the sector measure coefficients are significant, but the coefficients for services and manufacturing and trade – the sector groups with the largest number of jobs – are significant.

Overall, population, employment and transport access have different effects on total vehicle and truck volume densities. For total vehicle volume, employment variables and transport supply and access measures contribute much more than population variables to the variations of dependent variable. Truck volume is not always significantly related to transport access to major generators; we suspect that since areas around airports and seaports tend to be industrial zones, the employment variables capture some of their effect. Truck activity intensity is strongly and negatively associated with population density and household income. This makes sense: higher income households are likely to live further away from freight intensive activities, and although high population density creates demand for freight, locations with high population density – an indicator of high land price – would crowd out truck (and land) intensive activities such as warehousing and distribution.

5 CONCLUSIONS

We have presented the concept of a freight landscape and tested the hypothesis that these patterns are related to population, employment and access to transport infrastructure. We used network model data for both the Los Angeles region and San Francisco region, and estimated two sets of models, one using simple categories of combined population and employment density, and the other using separate measures of population and employment characteristics. We estimated models for both total vehicles and heavy trucks.

Our results are encouraging. Our analysis provides some preliminary evidence that population, employment, and transport supply and access measures explain total vehicle and truck flows. The results show that the effects of different groups of explanatory variables vary across total vehicle flows and truck flows, but they are largely consistent with our theoretical expectation of the freight landscape patterns. The freight landscape concept may be a promising approach to describe spatial patterns of freight flows with generally available proxies.

Our results provide several policy implications for freight planning.

First, in spite of different geography and definition of freight flows, we get consistent results from Los Angeles and San Francisco, which support our argument that simple population and employment measures may be effective proxies for the spatial variation of freight activities, as expressed by truck traffic. The concept of freight landscape contributes to our understanding of freight flows in urban planning. It may offer planning agencies a low cost way to integrate freight movement into the planning process.

Second, given that freight data is largely unavailable at the metropolitan area level, our results suggest that with simple measures of population, employment and transport access, we can generate a rough estimate of freight intensities across places. Using these simple measures may provide a ready tool for creating a general picture of spatial patterns of freight activities, especially for the many metro areas without access to actual freight data.

Third, freight flows behave differently from general traffic flows, and therefore freight flow management schemes should take these differences into account. For example, we find that freight activities are less sensitive to transport access but more dependent on general socioeconomic characteristics than general traffic, suggesting that we should carefully examine the effectiveness of any transport policies that affect both passenger and freight movement. Finally, an unexpectedly weak relationship between freight activities and transport access to the major freight generators merits more study. It is possible that our results reflect the location choices discussed in Chapter 2. Logistics firms are moving away from the freight generators including seaports, airports and intermodal facilities that are located in the metropolitan core, trading off access for lower land prices and more available land.

More research is needed to enrich our understanding of metropolitan freight flows. Much of the spatial variation in truck traffic remains unexplained, and our analysis was conducted with model generated data. With actual freight flow counts, we may be able to more accurately test our concept of freight landscape and shed light on the actual mechanism of freight behavior in response to urban structure. In addition, we have conducted a study of four metropolitan areas and obtained regression results from only two of them; studies of other metro areas would help to determine the extent to which the freight landscape concept may contribute to a better understanding of urban freight dynamics.

6 IMPLEMENTATION

We developed the concept of freight landscape in part as a response to the lack of data available to local and regional planners. If simple measures of employment and population characteristics adequately reflect freight activity, they can be used at a sketch planning level to provide the basis for improving our understanding of how freight activity varies within metropolitan areas, and hence develop more effective plans and policies to manage freight activity. Local planners would have a tool to inform zoning and building codes, street design, parking policy, and truck route designation.

The freight landscape concept may also be used to reduce data collection needs. For example, the sixteen population and employment density categories could be used as a sampling frame for empirical data collection on truck activity which could then be used as a representative sample for the metro area. Such a sample would greatly increase the accuracy of transportation planning models.

At this time, however, the freight landscape remains a concept. Although our results are encouraging, additional research and development would be required to generate a tool ready for planning practice. The concept needs more extensive testing. It should be tested in other metro areas with different size, industry composition, and function in the global economic network. It should also be tested with actual truck count and classification data, rather than model generated data.

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