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Evaluating light rail sketch planning: actual versus predicted station boardings in Phoenix

Christopher Upchurch · Michael Kuby

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Abstract In recent years, transit planners are increasingly turning to simpler, faster, and more spatially detailed "sketch planning" or "direct demand" models for forecasting rail transit boardings. Planners use these models for preliminary review of corridors and analysis of station-area effects, instead of or prior to four-step regional travel demand models. This paper uses a sketch-planning model based on a multiple regression originally fitted to light-rail ridership data for 268 stations in nine U.S. cities, and applies it predictively to the Phoenix, Arizona light-rail starter line that opened in December, 2008. The independent variables in the regression model include station-specific trip generation and intermodal–access variables as well as system-wide variables measuring network structure, climate, and metropolitan-area factors. Here we compare the predictions we made before and after construction began to pre-construction Valley Metro Rail predictions and to the actual boardings data for the system's first 6 months of operations. Depending on the assumed number of bus lines at each station, the predicted total weekday ridership ranged from 24,767 to 37,907 compared with the average of 33,698 for the first 6 months, while the correlation of predicted and observed station boardings ranged from $r = 0.33$ to 0.47. Sports venues, universities, end-of-line stations, and the number of bus lines serving each station appear to account for the major over- and under-predictions at the station level.

Keywords Transit · Light rail · Planning · Sketch planning · Ridership prediction · Travel demand

C. Upchurch · M. Kuby (✉)
Arizona State University, Phoenix, AZ, USA
e-mail: mikekuby@asu.edu

C. Upchurch
Prescott, AZ, USA
e-mail: chris.upchurch@gmail.com

Introduction

Forecasting of rail transit ridership has posed a substantial challenge to planners and modelers for decades. Early studies (e.g., Pratt et al. 1977, Mayworm et al. 1980, Pratt and Coople 1981; Pushkarev et al. 1982) pioneered route-level and system-level forecasting techniques using professional judgment, stated preference surveys, cross-sectional studies, and longitudinal studies (Boyle 2006). These methods were soon supplanted by four-step models involving sequential analysis of trip generation, trip distribution, modal split, and traffic assignment (Johnston 2004; Dickey 1983. These kinds of regional travel demand models forecast transit ridership in the context of aggregate origin–destination (O–D) flow patterns, transit route structures, and travel cost and time relative to other modes.

Forecasting light rail, however, poses some interesting challenges, especially with respect to the non-motorized part of door-to-door transit trips and the station-area effects (Cervero 2006). To address these weaknesses, regional modelers have modified the four-step approach in a variety of ways that attempt to take station accessibility, density, land-use diversity, and urban design into account by adjusting coefficients, inserting "sub-steps," and adding feedback loops or post-processing steps (Cervero 2006). Others have abandoned the aggregate, zone-based four-step approach entirely in favor of microsimulation models (Kitamura et al. 2000; Goulias 1997; Guhathakurta 2002; Smith et al. 1995; Waddell 2002).

While regional travel demand models were for many years the standard approach used for submission of ridership forecasts to the Federal Transit Administration (FTA) New Starts and Small Starts programs, there was no strict requirement to employ a four-step method. As far back as the early 1990s, the Urban Mass Transit Administration (UMTA), which preceded the FTA, accepted ridership forecasts developed using incremental, data-driven methods for rail projects in Baltimore and Honolulu. The current New Starts reporting criteria specifically include methodologies that involve "quality data paired with straightforward analysis," which under the "right circumstances" can provide a "more direct representation of travel than a regional model," which in fact "may be preferable to a regional-model-based approach" (FTA 2011, p. 9). The FTA itself has sponsored the development of the Aggregate Rail Ridership Forecasting (AARF) Model, which combines O–D trip data with GIS-based station buffer zones (FTA 2006).

The limitations of four-step models can also can also be addressed using station-level approaches, known as sketch-planning or direct-demand models, that take advantage of the availability of ridership data from recently completed projects (Ewing and Cervero 2001; Chu 2004; Boyle 2006; Cervero 2006). Transit agencies sometimes turn to simpler, faster, and more spatially disaggregated one-step models for predicting ridership based on statistical analysis of station-level boardings across one or more cities. Sketch-planning models are intended for quick, first-cut, order-of-magnitude analysis and a greater sensitivity to station-area effects than four-step models.

In this paper, we apply a sketch-planning model to the Phoenix, Arizona light-rail system, which opened in December 2008 amid substantial skepticism about whether light rail would succeed in a lower-density, automobile-oriented, polycentric city such as Phoenix. The sketch planning approach is based on a multiple regression model originally fitted to boardings data for 268 stations in nine U.S. cities (Kuby et al. 2004). The sketch-planning model incorporates a geographic information system (GIS) technique to compute station areas based on a half-mile walking distance, taking into account street geometry and off-network distances (Upchurch et al. 2004). The independent variables include population, employment, and socioeconomic status for each station area, as well as variables representing station-specific intermodal access and special trip generation factors, plus system-wide network structure, climate, and metropolitan-area factors.

This paper first reviews the ridership forecasting techniques developed since the 1970s. We then apply the fitted regression model predictively to the independent variables computed for the Phoenix Valley Metro Rail (VMR) system's starter line to forecast boardings by station in a one-step process. We then compare the model's predictions to the actual boardings achieved in the first half year of operation, as well as to the station-level predictions from Valley Metro's four-step model. Finally, we discuss these comparisons and draw conclusions.

Literature review

This review classifies forecasting methods into several categories: route-level or system-level approaches; four-step models; micro-simulation; and two kinds of station-level methods differentiated by whether or not they use O–D flow data. Those that do not, known as sketch-planning or direct-demand models, are the main subject of this paper.

For forecasting purposes, early studies by Pratt et al. (1977), Mayworm et al. (1980), and Pratt and Coople (1981) for the Federal Housing Administration (FHA) and Urban Mass Transportation Administration (UMTA) served as guidelines for a generation of transit planners (Boyle 2006). Pushkarev et al. (1982) conducted one of the first national assessments of corridors geographically suited for new urban rail. Menhard and Ruprecht (1983) reviewed early route-level forecasting techniques and classified techniques into four groups: professional judgment; stated preference surveys; cross-sectional studies; and longitudinal studies. The cross-sectional approach has been implemented by cross-sectional regression analysis as well as identifying peer cities or routes with similar characteristics (Boyle 2006). Ulberg (1982), Levinson (1985), Horowitz (1985) and Stopher (1992) are well-known examples of the regression approach to route-level forecasting. They used independent variables such as service levels, fares, total population, population density, employment, income, accessibility to stops, automobile ownership, and gasoline price, headways, and different types of bus connections. Peng et al. (1997) also considered interaction effects between transit supply and demand, and between different routes such that increases in one route can cause decreases in another.

By far the most common approach used over the last several decades to estimate transit ridership for the FTA New Starts and Small Starts programs has been the four-step Urban Transportation Model System (UTMS). This modeling is usually performed by the metropolitan planning organizations (MPOs), either in-house or by consultants, rather than by the transit agencies (Boyle 2006). UTMS is based on sequential analysis of trip generation, trip distribution, modal split and network assignment, and is used for a variety of transportation planning purposes. We refer readers to Johnston (2004) and Dickey (1983) for a review of the four-step process. Its strength is its ability to forecast transit usage in the context of the entire metropolitan region and in competition with other modes (Johnston 2004). While UTMS is used extensively for transportation planning, light rail poses some interesting challenges, especially in determining modal split and station-area effects.

As Cervero (2006) noted, "four-step travel demand forecasting models were never meant to estimate the travel impacts of neighborhood-level smart growth initiatives like transit villages, but rather to guide regional highway and transit investments" (p. 285), and by the same token may be too geographically coarse for predicting boardings at the station scale. Especially when introducing a new rail mode to a city, there are no data from an existing local system available to calibrate the model. Instead, four-step models must rely on data from a peer city that already has the new mode, but is otherwise similar. The choice of peer city can have a large impact on predicted ridership.

The level of spatial aggregation in both the TAZ geography and the intrazonal street network limits the ability of four-step models to predict walking to stations and the effect of urban design and transit-oriented development (TOD) on rail ridership (Cervero 2006). When planning an extension, the St. Louis MetroLink system revised its TAZ system by splitting zones near the proposed light-rail alignment into smaller areas (Kaplan et al. 2003). For the crucial mode choice step, Cervero (2006) noted that because walking and bicycling trips are usually left off the household surveys, nonmotorized trips are often "missing altogether" from four-step models. Finally, the time and effort involved in running the four-step model and revising it to run alternative rail configurations or different behavioral or land-use assumptions also makes it difficult to evaluate potential ridership under different scenarios.

Some planners have modified the four-step approach to address some of these shortcomings. Cervero (2006) classified these efforts into four general approaches. First, cities such as Austin TX, Portland OR, and Gainesville FL adjusted auto-ownership data based on factors such as proximity to stations, street geometry, and sidewalks, which then influences trip generation and modal split. Second, in Austin, Portland, and the San Francisco Bay Area, modelers have added a pre-modal-split stage to better model the non-motorized trips to transit stops. Third, MPOs such as Gainesville have linked the share of trips targeted to intrazonal destinations to the density, diversity, and design (the three Ds), and a number of regions now include a feedback loop after route assignment back to trip distribution to redirect some trips away from congested corridors. Fourth, Cervero noted that cities such as Sacramento have implemented feedback loops back to the land-use model that precedes trip generation in order to allow traffic congestion to influence location of economic activity. Cervero also reported on efforts to add a post-processing step to fine-tune four-step outputs after the fact.

Rather than try to retrofit four-step models, some researchers have turned to microsimulation to overcome the geographic, behavioral, and policy limitations of UTMS described above. A key element of microsimulation models is the notion that different trips made by the same individual on the same day are inextricably linked, and that time matters (Kitamura et al. 2000). Microsimulation models are generally disaggregated and activity-based (Goulias 1997), and explicitly model the process that generates the results (Guhathakurta 2002). TRANSIMS (Smith et al. 1995) and UrbanSim (Waddell 2002) are two of the more highly developed approaches. Some MPOs have begun using these kinds of models for practical transit ridership forecasting.

A simpler alternative approach integrating station-area data with O–D flow data is offered by the Aggregate Rail Ridership Forecasting (AARF) Model (FTA 2006; Woodford 2009). Specifically, AARF uses Census Transportation Planning Package (CTPP) journey-to-work data to estimate ridership potential based on residence-workplace TAZ pairs that both fall within concentric buffers drawn around different rail stations. AARF models have been fitted for both light rail and commuter rail. The ARRF approach is motivated by the availability of ridership data from recently completed projects and their ability to provide insights into ridership potential. Initially, the FTA cautioned that "forecasts from the model [were] not intended to replace carefully prepared forecasts from local travel models; rather, they provide another source of insights into the reasonableness of those local forecasts" (FTA 2006, p. 1), but as noted earlier, the FTA's New Starts reporting criteria now specifically permit travel forecasts to be developed on this basis.

While simpler and more transparent, the ARRF model continues to rely on O–D flows as the basis for ridership predictions. In contrast, this paper focuses on station-level "direct-demand" or "sketch-planning" models that predict boardings based on station-area characteristics without any O–D data. While no project sponsor has yet to submit a New Starts or Small Starts proposal based on these simpler and more spatially disaggregated one-step models (personal communication, FTA 2013), some transit agencies have begun using them for quick, first-cut tests of corridor alignments and station arrangements before more-detailed analysis of the best alternatives using more sophisticated approaches. Another appeal of sketch-planning models is their perceived greater sensitivity to station-area effects. Parsons Brinckerhoff Quade & Douglas, Inc. (1996) conducted one of the first station-level analyses of multiple rail systems and argued that these techniques ''bypass the usual four-step travel demand modeling process with a simplified approach that estimates travel demand directly, incorporating trip demand, mode choice, trip distribution, and traffic assignment features''(p. E-2).

Sketch planning or station-level regression models have used a wide variety of independent variables to explain station boardings (Ewing and Cervero 2001; Chu 2004; Boyle 2006; Cervero 2006). Variables such as population, employment, bus service, and park-and-ride stops are common elements of most models (e.g. Saur 2004). Kuby et al. (2004) used 17 independent variables grouped into five categories: (1) traffic generation; (2) intermodal connection; (3) citywide; (4) network structure; and (5) socioeconomic status. A noteworthy element of their approach was use of a city-wide climate variable, heating plus cooling degree days, which measures total accumulated degrees below (above) a 65 °F base temperature and is included to account for uncomfortably hot and cold outdoor temperatures for walking to and waiting for transit. Sohn and Shim (2010) used multiple regression and simultaneous equation modeling to explain station boardings on the Seoul Metro. They categorized their variables into five somewhat similar groups: (1) trip generation; (2) external connectivity (to both rail and road); (3) built environment; (4) intermodal connection; and, (5) socioeconomic status. Notable innovations included several centrality indices adopted from the complex networks literature. These metrics measured the centrality of Seoul metro stations within both rail and highway networks in terms of being close to other nodes, between other nodes, and the straightness of the network path to it from other nodes. Estupiñán and Rodríguez (2008) developed a simultaneous equation model for bus rapid transit (BRT) boardings that included variables categorized into (1) station characteristics; (2) physical attributes including various sidewalk metrics; (3) perceived characteristics such as cleanliness and safety; and (4) neighborhood attributes such as violent deaths, theft, unemployment and population and road density.

Researchers have included other relevant categories of variables. Ewing (1996) and Chu (2004) included land-use diversity variables to explain bus-stop boardings. The Transit Boardings Estimation and Simulation Tool (T-BEST) developed for the Florida Department of Transportation (2010) accounts for connectivity, accessibility, service levels, and feeder routes as well as competing routes. T-BEST is notable for predicting boardings for different times of day and for considering upstream and downstream stops with similar destinations and activities as well as various forms of impedance such as transfer walk times, wait times, and fares. Lane et al. (2006) also considered service variables such as fares, speeds, and headways. Taylor and Fink (2003), however, reviewed the literature and concluded that factors "internal" to the transit system are less important than the "external" factors such as surrounding land use and population; that is, the type of service seems to matter less than the areas it serves.

Street patterns and urban design factors have been incorporated in a number of ways. Sohn and Shim (2010) considered intersection density and other measures of street patterns as independent variables. In other studies, street patterns were not included directly via an independent variable, but were indirectly included via the method used to define the catchment or service area of each station. For instance, rather than use circular buffers around each station, Kuby et al. (2004) generated mutually exclusive service areas based on the shortest network-based walking distance, and then computed population, employment, and other independent variables for those station areas.

Yet another dimension on which sketch-planning models vary is whether a monocentric or polycentric approach is taken with respect to stations in the CBD. The Parsons Brinckerhoff (1996) model and the updated study by Lane et al. (2006) explained boardings only at non-CBD stations considering accessibility of stations only to the CBD, and included an independent variable for employment only in the CBD. Most of the later papers took a more polycentric approach and considered employment around non-CBD stations, population around CBD stations, and accessibility to all stations.

Despite the increasing interest in this approach, few comparisons of actual to predicted boardings at the scale of individual stations have been published in scientific journals. Lane et al. (2006) reported the R^2 values for the relationship between the forecasted and observed light-rail boardings at non-CBD stations for three different cities, but not by station. Kaplan et al. (2003) compared their forecasts with observed boardings by station for the Illinois segment of the St. Louis MetroLink, but the predictions were from a four-step model, not a sketch-planning model.

Boyle (2006) surveyed transit agencies about their experiences with various methods. These agencies were most frustrated by lack of, and reliability of, ridership data at the station or stop level. About 1/3 of agencies surveyed were satisfied, another 1/3 partly satisfied, and another 1/3 dissatisfied with their forecasting methods. Despite the growing sophistication of the simpler, less formal sketch-planning models, they are still used mainly for analyzing the effects of small-scale service changes and route modifications. Of the agencies surveyed, only 29 % reported that O–D trip data played a major part in ridership forecasting. Two-thirds reported using multiple methods for ridership forecasting. Of these, 20 % reported using regression analysis and 51 % using four-step models, but both methods were dwarfed by 80+ % using professional judgment, rules of thumb, and analogous situations.

Methods

The boardings predictions in this study are based on the Light-Rail Boardings Regression (LRBR) model developed by Kuby et al. (2004). That model was developed using data from nine light-rail systems throughout the United States, encompassing both traditional, monocentric cities such as Buffalo and Baltimore, and polycentric urban areas with urban morphologies more similar to Phoenix, including San Diego and Sacramento. The systems studied include Baltimore, Buffalo, Cleveland, Dallas, Portland, Sacramento, St. Louis, Salt Lake City, and San Diego. Together these light-rail systems had a total of 268 stations. Each station was an observation in the regression model. Since the study by Kuby et al. (2004) was able to use a single regression model to explain the boardings on light-rail systems in the widely varying conditions of these cities, the resulting LRBR model can be used to predict light-rail boardings in a similarly broad range of circumstances.

The dependent variable in the LRBR mode is the average number of weekday unlinked trips boarding at each station. The eleven independent variables represent statistically significant factors that influence light-rail boardings. These variables can be grouped into those that represent the features of individual station-area geography, those that represent the station's relative location in the light-rail network, those that indicate a station's connectivity to other modes, and those that apply to the entire system as a whole. Table 1 shows the eleven variables, the mean value of each non-dummy variable, and the regression model outputs.

As noted in the literature review, population and employment within the immediate area of the station have long been known to be important contributors to ridership, and these two variables are both significant with positive coefficients. The socioeconomic status of the population in the immediate area makes a significant positive difference in boardings as well. All three of these station service area factors are based on a half-mile walking distance around each station. The service areas are calculated using a network-based algorithm called the Linked On–Off Network (LOON) method, described in more detail below (Upchurch et al. 2004).

Table 1 LRBR regression coefficients from Kuby et al. (2004)

Variable group	Independent variable	Definition	Mean value[a]	*b* coefficient	*t* ratio	Significance
Station area	CONSTANT			1,583.82	4.178	0.0000
	EMPLOYMENT	Employment within walking distance	3,899	0.02294	2.024	0.0440
	POPULATION	Population within walking distance	1,490	0.09156	2.307	0.0219
	PCT_RENT	Percent of renters within walking distance	0.63	623.87	3.990	0.0001
Network location	TERMINAL	Station at end of line (1 yes, 0 no)		660.42	3.489	0.0006
	TRANSFER	Transfer station (1 yes, 0 no)		5,734.83	4.622	0.0000
	CENTRALITY	Normalized average travel time to all other stations[b]	0.64	−1871.77	5.256	0.0000
Intermodal connectivity	AIRPORT	Airport station (1 yes 0 no)		914.54	2.460	0.0145
	PARK&RIDE	Park-and-ride spaces at station	143	0.77415	3.519	0.0005
	BUS	Bus lines connecting to station	3	122.88	6.577	0.0000
Systemwide	DEGREE_DAYS	Average monthly heating and cooling degree days	404	−1.5169	3.518	0.0005
	EMPLOY_COV	Percent of PMSA employment w/in walking distance of all stations combined	0.18	1,300.99	1.933	0.0543

[a] For 268 existing stations in nine cities in Kuby et al. (2004)

[b] Normalized by dividing by the value for the station with the highest average travel time (i.e., most inaccessible station = 1.0)

The position of a station within the network has an effect on boardings. Stations near the center of the network are more easily accessible, and have easier access to all other stations, increasing their boardings. Conversely, those at the terminus of a line draw riders from the entire area beyond the end of the line, giving them greater boardings. The standard method of counting boardings for light-rail systems is the unlinked trip, meaning riders transferring between one line and another are counted as an additional boarding. To account for this, the model includes a transfer station variable for stations at the intersection of two light-rail lines.

A station's accessibility by other modes is a major contributor to its boardings. The number of park-and-ride spaces contributes to boardings, often from beyond the half-mile walking distance, as does the number of bus lines that pass within a block of the station. Stations that serve a major airport have higher boardings as well, although this functions more in the role of a destination and trip attractor than as part of an intermodal system.

While most variables are concerned with station-level variation, the LRBR includes two that are constant across each light-rail system. First, the average monthly degree-days variable is a measure of climate. Kuby et al. (2004) hypothesized that hot and cold climates tend to discourage ridership by making it less comfortable to walk to or from light-rail stations and wait for the next train, discouraging ridership, while more temperate weather encourages it. The degree-days variable was not only significant, it had a large negative coefficient, amounting to a difference of more than 600 daily boardings at each station between the most temperate climate in the study (San Diego) and the most extreme (Buffalo). Second, light-rail systems are influenced by a critical mass or network effect: the greater the proportion of an urban area's attractions that are accessible via the system, the more useful the system is for riders. The employment coverage variable represents this effect using the percentage of metropolitan area employment within half a mile of any light-rail station as a proxy for this coverage.

As mentioned above, the station-area variables are based on half-mile walking distance service areas created via the LOON method. The LOON method is a raster-based algorithm for creating network-based mutually exclusive service areas around facilities. The method calculates distance from to each cell to the nearest facility by travelling directly to the nearest portion of the street network, then travelling along the street network to the nearest station. The raster-based nature of the algorithm makes it easy to enforce mutual exclusivity, preventing the service areas of adjoining stations from overlapping and leading to double counting of population or employment.

The LRBR and LOON methods were integrated into a Spatial Decision Support System (SDSS) called the Rail Alignment Planning Tool (RAPT). A SDSS is a software system designed to help decision makers solve semi-structured problems (Malczewski 1997), such as locating light rail stations. RAPT is built on top of ArcGIS and allows a planner to locate light rail stations, define their properties, link them together into lines to create a network, and calculate the predicted boardings for a set of stations and network configuration.

Case Study

The Phoenix light-rail system is composed of 28 stations, arranged in a roughly "L" shape (see Fig. 1). The northern end of the L is at Spectrum Mall, and includes stations with several large park-and-ride lots along Camelback Road. It then turns south on Central Ave. passing several high schools, a major hospital complex, high-rise apartments and offices, major museums and the main public library. The corner of the L is in downtown Phoenix, including a large transit center and a station serving the baseball and basketball arenas in

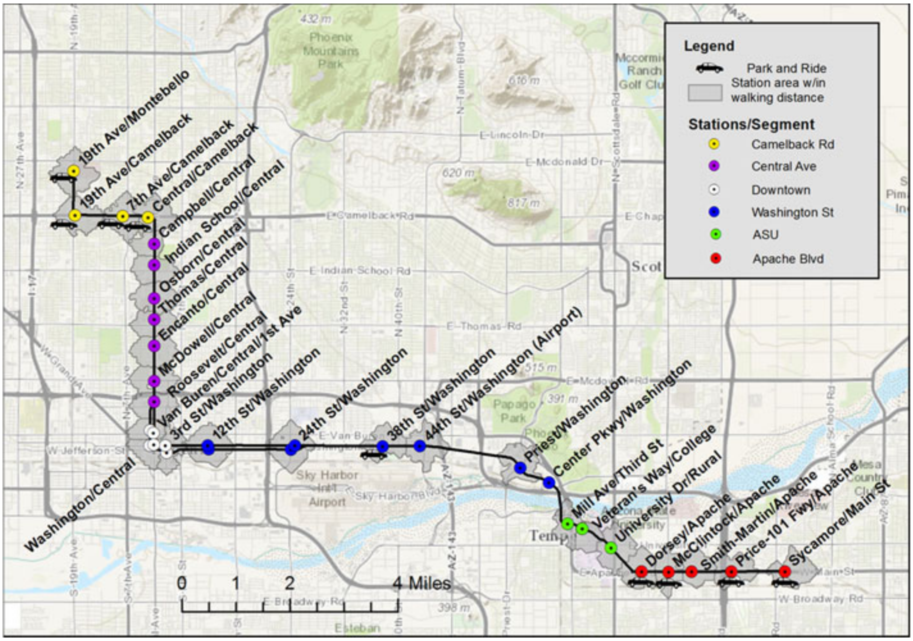

Fig. 1 Overview of the Phoenix area light-rail system, including stations and the half-mile walking distance buffers generated via the LOON method

the downtown area. The eastern leg of the L travels down Washington and Jefferson Streets through semi-industrial and low-income areas before passing by a community college, Sky Harbor airport, and associated hotels and offices. It then crosses an artificial lake in the Salt River channel to downtown Tempe, skirts north of Arizona State University's main campus, and travels along Apache Boulevard through an area of Tempe with large populations of students and renters until ending in the westernmost edge of Mesa, AZ. The alignment serves some relatively high-density residential areas near both ends of the line (Fig. 2a). It also passes through corridors of high-density employment, on both the north/south and east/west legs of the L (Fig. 2b).

Our original predictions for light-rail boardings in Phoenix were made in 2004–2005. At the time, we had to contend with some limitations on the available data. All of our population and employment data were from 2000, making it almost 9 years out of date by the time the Phoenix light-rail system began operating. In the intervening years, the number of people living and working near the light-rail station locations increased not only through natural growth, but also due to TOD around the station areas (Atkinson-Palombo and Kuby 2011).

The bus lines variable presented an even greater difficulty. The opening of the light-rail line would spur a reorganization of Valley Metro's bus lines, but the new configuration had not yet been publicly released. Many of the existing bus lines paralleled the planned light rail alignment, and we anticipated that some of these would be eliminated once the light-rail began operation. Even if they remained in operation, however, each route would not be likely to contribute 123 boardings per station per day at each of five stations in a row. To address this issue, we made predictions using both the Valley Metro bus system as of 2004,

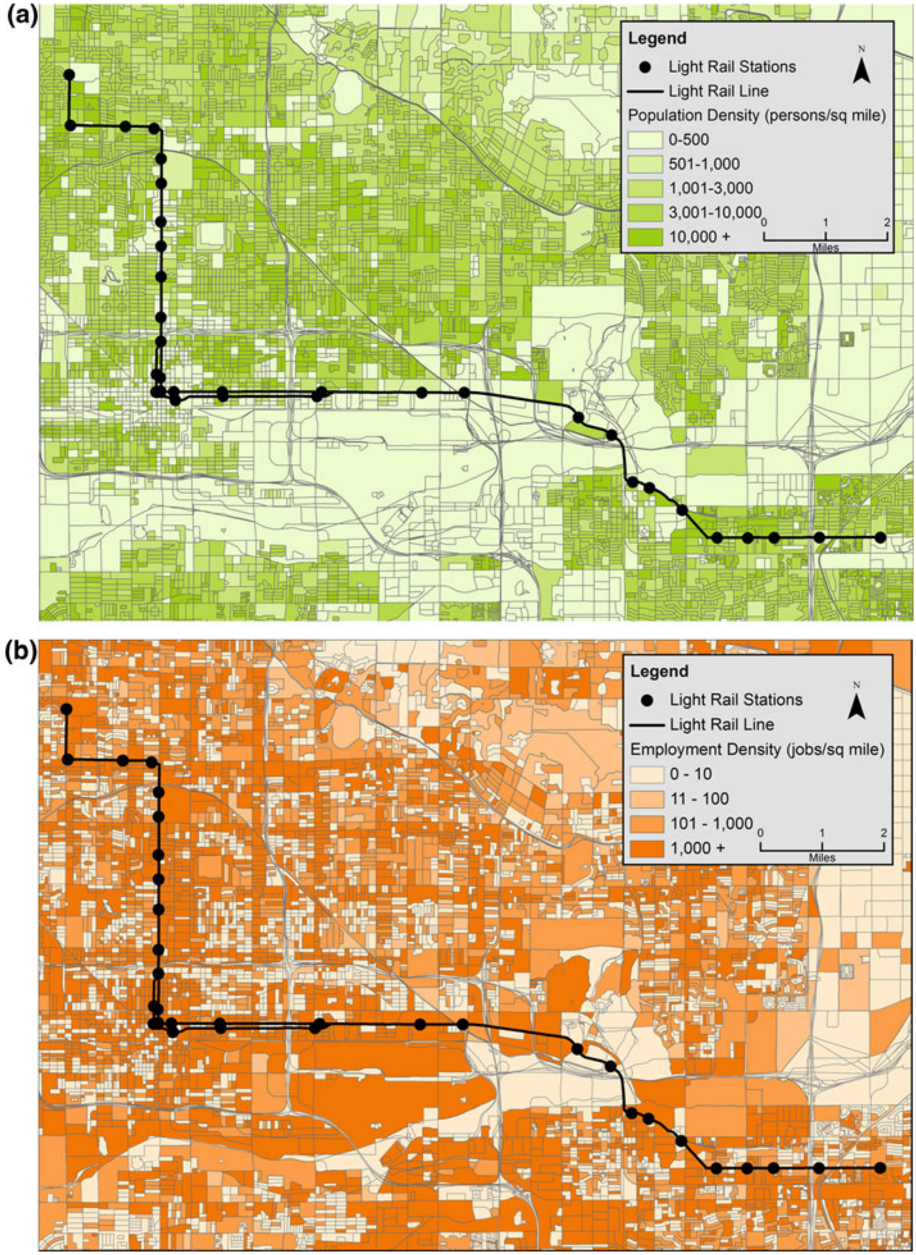

Fig. 2 Employment density (**a**) and population density (**b**) for the area around the light rail line

and using adjusted bus line data counting bus lines only at the first or last station where they intersect the light-rail line or at a transit center if the lines serve one.

Now that the light-rail system has entered service, the new bus system configuration is available as well. We feel that the actual numbers of bus lines in the post-light-rail configuration are the best representation of the bus variable, both because they are most comparable to the situation in the cities that the LRBR was based on (i.e. post-reorganization), and because a transit agency using the LRBR predictively would have a good idea how the bus system would be re-configured after a new light-rail system is introduced. Therefore, the predictions based on the actual 2010 bus system configuration are the primary focus for the remainder of the paper, but we also include results for the other two forecasts using the other bus line counts in the interest of full disclosure, since they are the estimates we made prior to the opening of the system. The predictions using post-opening bus lines also use the actual numbers of park-and-ride spaces, which differ slightly from the numbers planned in 2005. Contemporaneously with our boardings predictions, Valley Metro released their own official opening-day boardings predictions, based on the Maricopa Association of Governments' (MAG) four-step regional transportation model.

Results and discussion

Table 2 compares these four sets of predictions to the actual average weekday boardings during the first and second quarters of 2009 (the system began operation on December 27, 2008). All of the predictions were made before Valley Metro decided to include a station at Center Parkway and Washington, thus none of them include that station. During the first two quarters of 2009, the Valley Metro light-rail system had an average of 33,698 weekday boardings. Our original 2005 prediction and the updated prediction using the actual bus lines are somewhat higher, at 37,547 and 37,907 daily boardings, respectively. The Valley Metro prediction and our 2004 prediction using the adjusted bus lines are substantially lower, at 26,065 and 24,767 daily boardings respectively. While our prediction with the adjusted bus lines was furthest from the actual results in absolute terms, under-predicting it by 8,931 boardings, it has the highest correlation with the actual boardings, at 0.47. This is followed by the Valley Metro prediction at 0.43, our prediction using actual bus lines at 0.37 (which is our focus for the remainder of the paper), and our prediction using the 2004 bus lines at 0.33. None of these correlations are particularly strong.

As seen in Fig. 3, the differences between the actual boardings and our predictions using actual bus lines and completed park-and-ride spaces are dominated by seven very poorly predicted stations. We massively over-predict boardings at two downtown stations, and under-predict boardings at the two terminal stations, the station that serves Phoenix's downtown sports venues, and two of the stations that serve Arizona State University.

The largest differences between our predictions and actual boardings came at two downtown stations. We predicted more than 5,000 riders for each of these stations, yet they averaged 2,021 and 1,525 riders respectively. Each of these stations is actually a pair of stations on either street of a one-way pair. The Central Station Transit Center where Van Buren St. crosses Central Ave. (northbound) and 1st Avenue (southbound) is served by 34 bus lines, more than any other station on the system. Most of these bus lines also pass by the Washington/Central Ave station pair a few blocks to the south. These massive concentrations of bus lines are responsible for the extremely high boardings predictions for these two pairs of stations. The bus line variable in the LRBR model has a b-coefficient of 123 additional boardings per bus line at a station. This would mean that the 34 bus lines serving the Van Buren station should result in 4,178 riders, not counting the other variables.

Clearly, these bus lines are not contributing riders in the numbers that the LRBR model predicts. In part, this is probably due to the fact that most bus lines serve both station pairs, making the connections largely redundant. It may also be due in part to the stations'

Table 2 Predictions and actual boardings

Station names	Station area features	Line segment (corridor)	Actual boardings	Valley Metro rail prediction	LRBR predictions[a]		
					2004 bus lines	Adjusted bus lines	Actual bus, P&R[c]
19th Ave/Montebello	End of line, TC, P&R	Camelback	3,338	2,226	1,770	1,770	1,869
19th Ave/Camelback	P&R	Camelback	991	2,120	1,558	1,313	1,075
7th Ave/Camelback	P&R	Camelback	647	538	1,238	624	747
Central/Camelback	TC, P&R	Camelback	472	961	1,365	874	1,262
Campbell/Central		Central	734	839	1,146	286	900
Indian School/Central		Central	1,154	1,068	1,608	748	1,362
Osborn/Central		Central	820	395	1,460	600	1,214
Thomas/Central		Central	1,354	754	1,861	1,001	1,615
Encanto/Central		Central	498	301	1,228	368	982
McDowell/Central		Central	1,352	834	1,568	708	1,322
Roosevelt/Central		Central	1,498	750	1,794	811	1,548
Central Station (Van Buren/Central/1st Ave)	ASU Downtown Campus, TC	Downtown	2,021	2,116	3,919	3,551	5,025
Washington/Central[b]		Downtown	1,525	409	4,034	1,700	5,140
3rd St/Washington	Sports Stadiums	Downtown	1,950	189	746	500	500
12th St/Washington		Washington	488	780	1,056	810	1,179
24th St/Washington		Washington	574	703	947	824	947
38th St/Washington	P&R	Washington	264	523	726	603	995
44th St/Washington	Airport	Washington	1,677	240	1,508	1,385	1,768
Priest/Washington		Washington	1,047	677	819	574	819
Center Pkwy/Washington		Washington	274	n.a.	n.a	n.a.	n.a.
Mill Ave/3rd St		ASU	1,645	910	880	266	758
Veterans Way/College	TC	ASU	1,559	399	1,976	1,976	1,976

Table 2 continued

Station names	Station area features	Line segment (corridor)	Actual boardings	Valley Metro rail prediction	LRBR predictions[a]		
					2004 bus lines	Adjusted bus lines	Actual bus, P&R[c]
University/Rural		ASU	1,687	707	1,023	531	900
Dorsey/Apache	P&R	Apache	712	2,902	749	749	826
McClintock/Apache	P&R	Apache	982	540	744	621	744
Smith-Martin/Apache		Apache	318	857	217	94	217
Price-101 Fwy/Apache	P&R	Apache	715	715	577	454	655
Sycamore/Main St	End of Line, TC, P&R	Apache	3,402	2,612	1,029	1,029	1,561
Total[a]			33,698	26,065	37,547	24,767	37,907
Correlation with actual boardings				0.43	0.33	0.47	0.37

TC transit center, *P&R* park-and-ride

[a] Totals may not sum due to rounding

[b] From Washington/Central to 24th/Washington, all stations consist of two one-way stations, with the westbound station on Washington St. and the eastbound station on Jefferson St. one block to the south

[c] We view this prediction based on the reconfigured post-opening-day bus lines and actual park-and-ride spaces, which a transit agency would likely know in advance, as the prediction most representative of model performance. These are the predictions primarily discussed in the text, and the basis for the over- and under-predictions in Fig. 3

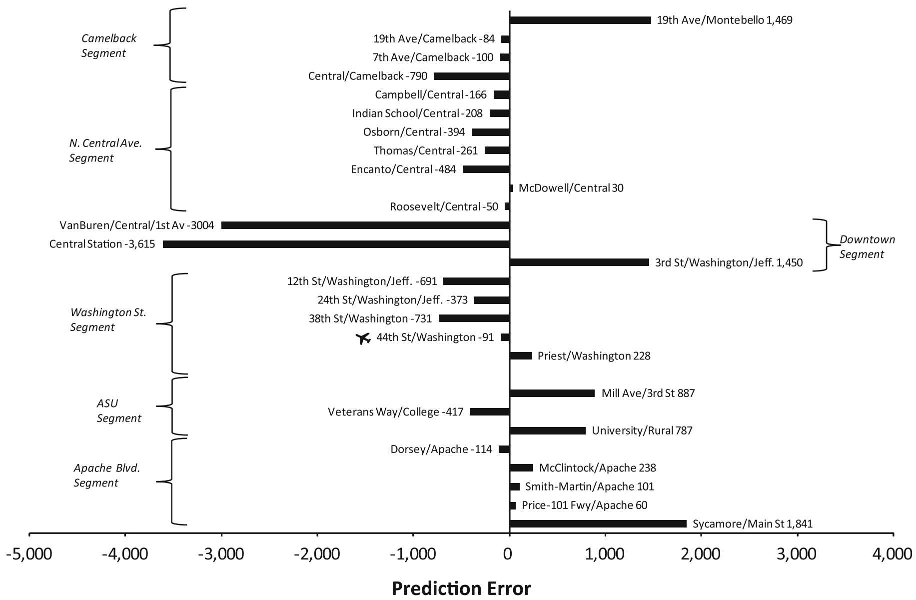

Fig. 3 Difference between actual boardings and our predictions using the actual bus lines and park-and-ride

location within the transit network. Even in a polycentric city such as Phoenix, downtown is still a major destination, and bus connections are correspondingly less important for generating light-rail boardings in major CBDs than at stations that feed riders into the system. The lower boardings at stations with many bus lines may also reflect Valley Metro's bus service in general.

Perhaps the most striking cases where actual boardings exceeded our predictions occur at the terminal stations at either end of the line. Actual boardings at the northern terminus (19th Ave/Montebello) are almost 1,500 riders higher than our prediction. Boardings at the eastern terminal station in Mesa (Sycamore/Main St) are more than 1,800 higher than predicted. The B-coefficient on the terminal variable in the LRBR should add 660.42 riders at these final stations, but this clearly does not capture the full magnitude of the end-of-the-line effect on the Phoenix system. The Valley Metro predictions for the terminal stations are higher than ours, but they still fall short of the actual boardings. The terminal station effect in Phoenix seems to be unusually large and merits further investigation. Valley Metro planners communicated to us that their model assumed a catchment area extending eight miles beyond the terminal stations but ridership surveys were showing that about one quarter of the riders were coming from as far away as 16 miles.

While the discrepancies at the terminal and downtown stations came as a surprise, the higher than expected boardings at the 3rd St/Washington station did not. This station serves the US Airways Center and Chase Field, Phoenix's professional basketball and baseball venues. A sports facility variable was considered during the development of the LRBR, but it was not included in the final analysis because, in some of the cities, much of the boardings data that made up the dependent variable were not collected, or collected irregularly, during sports seasons. In contrast, the National Basketball Association (NBA) season was ongoing during the first quarter of 2009 and part of the second, when the actual boardings data were collected. The Major League Baseball (MLB) baseball season began

April 6, 2009. The effect of sporting events on this pair of stations is illustrated by the increase of 43,519 boardings (an average of 478 per day) from the first quarter to the second quarter, when the baseball season overlapped with the basketball season. While data issues prevented the inclusion of a sports-venue variable in the LRBR, the higher than predicted boardings at 3rd St/Washington reinforces the importance of sporting events to transit ridership.

Although not as large as the over- or under-predictions already discussed, the higher than expected boardings at the Mill Ave/3rd St and University/Rural stations in Tempe are also of note, as these are two of the three stations serving Arizona State University. Much like with sports venues, a potential university variable in the LRBR did not prove significant. We speculate that that this was because some boardings data were collected when school was not in session and the college enrollment data for the nine cities did not distinguish between commuter students and those who live on campus. ASU was in session for most of the first quarter of 2009 and approximately half of the second quarter. Total ridership during the second quarter was down at all three ASU-area stations by about 10,000 boardings each (or about 110 boardings per day), due to summer break and lower summer enrollment. The third ASU light rail station at Veterans Way/College had a much higher prediction than the other two stations (1,976 vs 758 and 900), largely due to a very high concentration of dormitories in its service area giving high values for the population and percent renters variables. This meant that the final boardings were not under-predicted as were the other two stations.

Other than confirming that they were generated using a four-step model, VMR was unwilling to share details about the process behind their station level predictions, limiting our ability to speculate about the causes of their over- and under-predictions at specific stations. As with our results, they under-predicted boardings at the terminal stations. They also join us in under-predicting boardings at the 3rd St/Washington station near the basketball and baseball arenas and two of the Arizona State University stations. In contrast to our massive over-prediction at the downtown Van Buren/Central/1st Ave and Washington/Central stations, VMR under-predicted boardings by more than 1,000 riders. They also under-predicted boardings at the 44th St/Washington station where the light-rail system connects to the airport shuttle. The two largest VMR over-predictions are particularly difficult to explain. They over-predicted boardings at 19th Ave/Camelback and Dorsey/Apache by more than 1,000 and 2,000 riders, respectively. While the lack of specifics on the VMR model make it difficult to hypothesize about the causes of their mispredictions, some of them seem to be associated with the same factors as our largest over- and under-predictions: downtown stations, sports arenas, universities, and terminal stations.

In addition to focusing on the most poorly predicted types of stations, it is useful to attempt to generalize about the model's performance by rail line segment (Figs. 1, 3; Table 2) in search of any consistent patterns. The downtown Phoenix, ASU, and terminus stations were discussed earlier and are omitted from the following discussion.

- The stations in the Camelback Road segment in Phoenix are generally over-predicted by our model. Our other models using older bus line configurations, as well as Valley Metro's model, also over-predicted these stations most of the time. This is an auto-centric landscape including strip malls and motels that has seen very little TOD and is not attractive for walking to stations.
- The North Central Ave segment features Phoenix's first-ever shopping mall and numerous high-rise buildings that extend downtown Phoenix linearly and discontinuously north on Central Ave. With the exception of one slightly under-predicted station

at McDowell/Central near the Phoenix Public Library and Art Museum, all stations are generally over-predicted by two of our models, except for the one that adjusts for the same bus line passing multiple stations in a row. Valley Metro's model generally under-predicted these stations. In addition to bus lines, large surface parking lots and garages for the businesses along the corridor may negatively impact the ridership.

- The Washington St. segment is fairly industrial and lower-income until it reaches the airport, and all four models including Valley Metro's over-predict the 12th, 24th, and 38th St. stations, despite the presence of a large community college at 38th St/Washington. The airport station (served by a shuttle bus until an automated, elevated, rubber-tired people mover was opened in April 2013) was closely predicted by our model regardless of bus line assumption, but highly under-predicted by VMR's four-step model. Beyond the airport on Washington St., all four models somewhat under-predict the Priest/Washington station that features an "edge-city" suburban office complex surrounded by low-income neighborhoods.
- Finally, the Apache Blvd segment travels through heavy student and renter neighborhoods in Tempe until terminating just across the Tempe–Mesa border. Except for the terminus station that was hugely under-predicted, these Apache Blvd stations were predicted fairly accurately, though slightly under-predicted.

These observations regarding the sketch-planning model's ability to predict boardings along each segment of the line suggest that such models should perhaps include factors such as TOD, parking availability at trip attractors (as opposed to park-and-ride), type of employment, and walkability (Estupiñán and Rodríguez 2008) that were not included in our model.

Some discrepancies between model predictions and actual boardings may be due to temporal inconsistencies. The coefficients of our predictive model are based on fitting the boardings data in the nine other cities with relatively mature systems in 2000 using 2000 census and jobs data. We compare our predictions to the first two full quarters of operation of the VMR system in 2009, however, because the VMR station-level predictions were specifically "opening day" forecasts. Since the opening of the VMR system, ridership has continued to grow steadily, from under 35,000 unlinked trips per weekday in 2009 to over 43,000 in 2012. Among the factors likely to be contributing to that growth are the maturation of the system, increasing familiarity with it in the general population, economic recovery, rising gasoline prices, expansion of the ASU Downtown campus, and continuing construction of TOD along the line.

Conclusion

This paper demonstrates the use of a station-level, regression-based, sketch-planning model for predictive purposes using station area, network, and city-wide independent variables, without requiring any O–D flow data. We used the model to predict boardings for the Phoenix-area light rail system before construction began, and again afterwards using the same model with the post-construction reconfigured number of bus lines and park-and-ride spaces. We then compared our predictions to the actual boardings data for the system's first 6 months of operations, as well as to Valley Metro Rail's pre-construction boardings predictions, at three levels: for the starter system as a whole, for six segments of the line, and at the most poorly predicted stations. The correlation coefficient (r) of the various predictions to the actual station boardings was in the range of 0.33–0.47. While not great, our r values were on par with the r of 0.43 for Valley Metro's predictions developed using a four-step regional travel demand model, and were developed with considerably less expense and greater transparency. In addition, given that station-level sketch-planning research is a relatively recent development, and that this paper appears to be the first that compares predicted boardings to actual, we think there is considerable room for improvement of the goodness-of-fit. Based on the over-predictions and under-predictions of boardings, a number of areas of improvement can be highlighted for developing better direct-demand models for future use.

The largest over- and under-predictions in Phoenix can be divided into four categories: downtown stations with numerous bus lines, terminal stations, university stations, and stations with sports arenas. Of these, the difficulty predicting boardings at the university and arena stations was expected because of the problems with the available data encountered by Kuby et al. (2004) when they attempted to include variables representing these factors. The period when ridership data were collected often did not correspond with the sports season or school year. The under-prediction of boardings at the university and arena stations in this study reinforces the need for research, data, and properly operationalized variables for incorporating colleges and sports arenas in future sketch-planning models.

The poor prediction of boardings at the downtown transit center was also not surprising, but for a different reason. Our predicted boardings were far higher than the actual, mainly because of the large number of bus lines, most of which stop at both over-predicted downtown stations. While we are not sure how generalizable this problem would be, future sketch planning models (and the regression models on which they are based) should handle parallel bus lines with great care, and possibly discount their impact in some way. However, there is another reason why the large discrepancies at some downtown stations was not surprising. In the regression analysis of the nine cities on which this sketch model is based (Kuby et al. 2004), most of the poorly predicted stations were downtown stations. We note that Parsons Brinckerhoff (1996) and Lane et al. (2006) avoided developing a *single* regression equation to predict both CBD and non-CBD stations, which suggests the possibility of developing a separate regression model based on the sample of CBD stations only. However, with today's polycentric metropolitan areas, with edge cities and suburban downtowns, the line between CBD and non-CBD is blurred. The lesson for sketch planning, perhaps, is to try to include other factors that can be applied consistently to CBD and non-CBD stations alike to account for the unexplained variation. Kuby et al. (2004) speculated that non-included variables such as parking costs, traffic congestion, and densities within shorter walking distances might improve the prediction of the CBD stations.

In contrast to the downtown, sports, and university stations, the under-prediction at the terminal stations was entirely unexpected. The LRBR model, which was fitted to 268 stations in nine other cities, estimated that, all else being equal, each terminal station would generate 660 additional weekday boardings, but the two Phoenix terminal stations exceeded that by an additional 1,500–1,900 boardings. This may be due to unique factors in the Phoenix area, the exact nature of which remains unknown.

For the most part, the stations that our sketch-planning model failed to predict accurately were also poorly forecast by VMR's four-step model. Both models missed badly at sports arenas, the university, terminal stations and downtown stations. The sketch planning model, however, seemed to do a better job of predicting the airport station through the use of a simple airport dummy variable. Some of VMR's over-predictions do not seem to be connected with any specific station characteristic, and our ability to attribute causes to VMR's over- and under-predictions is limited by lack of details about their forecasting methodology.

Looking at the different segments of Phoenix's starter line, rather than individual stations, the patterns of over- and under-prediction suggests that the regression model used may not have accounted adequately for factors such as TOD, ample free parking availability at employment and shopping locations (as opposed to park-and-ride), type of employment, and poor walkability. More research is needed to determine whether over- or under-predictions of entire segments was due to omitting these or other variables, or to error introduced through the passage of time.

Both the original research data, and the population and employment data for Phoenix were gathered in 2000, 9 years before the Phoenix light-rail system began operation. The population and employment around the light-rail station locations has grown considerably in the intervening years (Atkinson-Palombo and Kuby 2011). In addition, there may have been fundamental changes in factors that affect transit use. For instance, the average real price of gasoline in 2009 was more than 50 % higher than in 2000 (Energy Information Administration 2010). These long-term changes in people's willingness to use transit may have a significant impact on ridership models that rely on historical data.

This paper is one of the first to apply a sketch-planning model fitted to a national data set of light rail systems to all stations (not just the non-CBD stations) in another city (not withheld from the original data set) and to compare the predicted and observed boardings for individual stations. Starting in 2001, the FTA began requiring agencies to conduct before and after studies, and The Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU) required FTA to report a summary of these studies to Congress annually. Studies that compare pre and post estimates are important in light of the work of Pickrell (1992), Wachs (1986), and Flyvbjerg (2002) that question whether systematic biases exist in overestimating benefits and underestimating costs in transportation projects. An additional advantage of using sketch-planning models for station-scale ridership forecasting is the transparency of the method and its ability to be reproduced and checked by other stakeholders.

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Author Biographies

Christopher Upchurch obtained a masters degree from Arizona State University in 2005 and a Ph.D. from University of Utah in 2008, both in geography, and has taught at University of South Carolina. His fields of interest are GIS, light rail, and time–space geography.

Michael Kuby earned a Ph.D. in geography from Boston University in 1988. At Arizona State University he is Professor in the School of Geographical Sciences and Urban Planning and Director of the Interdisciplinary Graduate Certificate Program in Transportation Systems. He serves on the editorial boards of the *International Regional Science Review* and the *Journal of Transport Geography* and is Location Area Editor for *Networks and Spatial Economics*. His areas of interest include light rail, alternative fuels, and carbon capture and storage.