TRANSPORTATION AND LAND USE POLICY ANALYSIS USING INTEGRATED TRANSPORT AND GRAVITY-BASED LAND USE MODELS

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ABSTRACT

Forecasting urban futures is of great importance to many in order to ensure adequate provision of public and private services and implement policies that guide demand while mitigating negative impacts. This study produces year-2030 predictions of land use and travel conditions across the Austin-Round Rock Metropolitan Statistical Area of Texas, by integrating a gravity-based land use model (modeled on Putman's ITLUP specification) with a standard travel demand model. The land use model cycles through job, household and land consumption estimates across traffic analysis zones, before feeding forward into a contemporaneous model of travel patterns.

To better understand the implications of different policies, three scenarios were generated: a business-as-usual scenario, congestion pricing-plus-carbon tax scenario, and an urban growth boundary (UGB) scenario. Results reveal how these transportation and land use policies may shape our land and travel futures, while illuminating challenges and pitfalls of the gravity-based approach to land use (including the accompanying land consumption model). Of particular interest is the fact that imposition of road pricing (roughly 5¢/mile) had almost no discernable effect on land use predictions, yet resulted in the same predicted reduction in regional VMT as the UGB policy (roughly 15%).

INTRODUCTION

For decades, the complexity of transport and land development processes has challenged urban planners, policymakers, land developers, transportation engineers, air quality modelers and others. Numerous factors drive land use change and interact in subtle ways (e.g., Veldkamp and Lambin 2001, Lambin et al. 2003). While the impact of land use patterns on travel demand and, thereby, network conditions is reasonably well understood (via the process of trip generation and attraction), long-term changes in land use patterns and the effects of transport policy and system investment on land development and use remains elusive. Nevertheless, most experts agree that transportation does play a role in land development, even in the mature and extensive networks of major urban regions within developed countries.

A variety of land use allocation and travel demand models have been developed using different modeling objectives and methodologies, and several have been applied, including Hunt's PECAS (Hunt and Abraham 2003), Kockelman's RUBMRIO (Kockelman et al. 2005), Martinez's MUSSA (Martinez 1996), Gregor's LUSDR (Gregor 2007), and Waddell's UrbanSim (Borning et al. 2007). National Cooperative Highway Research Program (NCHRP) Report 423A (PBQD 1999) described eight leading land use models and focused on assessing the impacts of transportation projects. Miller et al. (1998) identified key issues in developing "ideal" land use models based upon a detailed review of six such tools. The general consensus is that no model is ideal; the appropriateness and usefulness of any given tool varies under different situations. While a range of modeling approaches exist, most medium-size and smaller metropolitan planning organizations (MPOs) do not have the resources to conduct sophisticated analyses (Duthie et al. 2007). Therefore, it is useful to investigate the analytical capabilities of relatively simple methods that are more likely to be employed in practice.

Lowry's 1964 gravity model is one of the oldest modeling strategies (Putman 1983), and its variant, Putman's Integrated Transportation-Land Use Package (ITLUP) is probably the most widely applied model of U.S. land use to date (Putman 1995). Recently, the Federal Highway Administration (FHWA) supported the development of the Transportation Economic and Land Use Model (TELUM), which is a GIS-embedded version of ITLUP offering three components: a

*D*isaggregated *R*esidential *A*llocation *M*odel (DRAM® [1]), an *EMP*loyment *Al*location model (EMPAL®) and *LAN*d *CON*sumption model (LANCON). However, this free software has restrictions. For example, the average population per zone must lie above 3,000 (and is recommended to be below 10,000), and the documentation neglects details on the LANCON model as well as the parameter estimation (model calibration) process. To overcome these restrictions, MATLAB (MathWorks 2005) codes were developed, following the household and employment allocation equations in TELUM's User Manual (2005) and land use consumption equations from Putman's work (1991). While specification of these three components was designed to mimic Putman's ITLUP, actual model applications no doubt differ slightly from the proprietary software. Therefore, these coded components are referred to as RESLOC, EMPLOC, and LUDENSITY within the open-source gravity-based land use model (G-LUM) [2].

This study calibrated and applied RESLOC, EMPLOC and LUDENSITY equations to Texas's five-county Austin-Round Rock Metropolitan Statistical Area (MSA), and demonstrated the implementation of three distinct transportation and land use scenarios. A reasonably standard sequential travel demand model (TDM) was linked externally to the land use model system in order to update travel conditions and provide a well-defined series of related steps to all future household and employment forecasts (at five-year intervals). All together, the system of equations forms a reasonable straightforward integrated transportation-land use model (ITLUM).

The following sections discuss model specification, data sets used, transportation and land use policy scenarios examined, and the results of model calibration and applications.

MODEL SPECIFICTION

This section describes the mathematical specification of the three G-LUM components as well as the TDM structure.

RESLOC presumes that household location patterns are determined by current job locations, land availability, travel impedances between all zones, and the prior period's distribution of households. Household allocation/assignment across zones is guided by the residential attractiveness of each zone, measured as a function of (a) each zone's presently vacant yet developable land, (b) the proportion of developable land that already has been developed, (c) residentially developed land, and (d) current number of residents by type. The importance of these variables is determined via model calibration, using least squares, maximum likelihood estimation (MLE), maximum entropy (ME) or other methods. The specification is largely non-linear in nature, and calibration requires two time points of data on household and employment location patterns, with associated land use maps.

Similarly, EMPLOC forecasts the spatial distribution of jobs by category. Employment allocation is based on zonal attractiveness, as measured by prior-year employment and zone size. Prior-year population and travel impedances (to all zones) also impact employment distribution.

Finally, LUDENSITY uses three log-linear equations to estimate land consumption by type (residential, basic and commercial) in each zone. Variables determining land consumption include the forecasted spatial distributions of households and jobs, and prior-year land use conditions. Key equations for all three models are as follows:

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[1] DRAM and EMPAL are trademarks of S.H. Putman Associates, Inc.
[2] Open-source code for an earlier version of this G-LUM model (i.e., without the zone-level constraints that ensure reasonable predictions) is available at http://www.ce.utexas.edu/prof/kockelman/G-LUM_Website/homepage.htm.

Household Allocation (RESLOC)

$$N_{i,t}^{n} = \eta^{n} \sum_{j} Q_{j,t}^{n} \frac{W_{i,t-1}^{n} c_{i,j,t-1}^{\alpha^{n}} \exp\left(\beta^{n} c_{i,j,t-1}\right)}{\sum_{i} W_{i,t-1}^{n} c_{i,j,t-1}^{\alpha^{n}} \exp\left(\beta^{n} c_{i,j,t-1}\right)} + \left(1-\eta^{n}\right) N_{i,t-1}^{n} \qquad (1)$$

where

$$Q_{j,t}^{n} = \sum_{k} a_{k,n} \frac{E_{j,t}^{k}}{1-u_{k}} \qquad (2)$$

$$W_{i,t-1}^{n} = \left(L_{i,t-1}^{v}\right)^{q^{n}} \left(1+x_{i,t-1}\right)^{r^{n}} \left(L_{i,t-1}^{r}\right)^{s^{n}} \prod_{n'} \left[\left(1 + \frac{N_{i,t-1}^{n'}}{\sum_{n} N_{i,t-1}^{n}} \right)^{b_{n'}^{n}} \right] \qquad (3)$$

and $N_{i,t}^{n}$ is the number of households of type *n* residing in zone *i* at time *t*; $c_{i,j,t-1}$ is impedance (travel time and/or cost) between zones *i* and *j* at time *t*-1; $a_{k,n}$ is the number of type *n* households per type *k* employee in the study region; $E_{j,t}^{k}$ is employment (number of jobs) of type *k* in zone *j* at time *t*; u_{k} is the unemployment rate for job type *k*; $L_{i,t-1}^{v}$ is vacant developable land in zone *i* at time *t*-1; $x_{i,t-1}$ is the proportion of developable land already developed in zone *i* at time *t*-1; $L_{i,t-1}^{r}$ is residential land in zone *i* at time *t*-1; and $\eta^{n}, \alpha^{n}, \beta^{n}, q^{n}, r^{n}, s^{n}$ and $b_{n'}^{n}$ are parameters estimated in model calibration. In addition, $Q_{j,t}^{n}$ converts employment to households, and $W_{i,t-1}^{n}$ represents the attractiveness of zone *i* for household type *n* at time *t*-1.

Employment Allocation (EMPLOC)

$$E_{j,t}^{k} = \lambda^{k} \sum_{i} N_{T,i,t-1} \frac{M_{j,t-1}^{k} c_{i,j,t-1}^{\omega^{k}} \exp\left(\rho^{k} c_{i,j,t-1}\right)}{\sum_{j} M_{j,t-1}^{k} c_{i,j,t-1}^{\omega^{k}} \exp\left(\rho^{k} c_{i,j,t-1}\right)} + \left(1-\lambda^{k}\right) E_{j,t-1}^{k} \qquad (4)$$

where

$$M_{j,t-1}^{k} = \left(E_{j,t-1}^{k}\right)^{a^{k}} \left(L_{j}\right)^{b^{k}} \qquad (5)$$

and $N_{T,i,t-1}$ is total households in zone *i* at time *t*-1; L_{j} is the total area of zone *j*; $\lambda^{k}, \omega^{k}, \rho^{k}, a^{k}$ and b^{k} are estimated in model calibration; and $M_{j,t-1}^{k}$ represents the attractiveness of zone *j* for employment type *k* at time *t*-1.

Land Consumption Rates (LUDENSITY)

$$\frac{L_{r,i,t}}{N_{T,i,t}} = k_0 L_{D,i,t-1}^{k_1} \left(\frac{L_{d,i,t-1}}{L_{D,i,t-1}}\right)^{k_2} \left(\frac{L_{b,i,t-1}}{L_{D,i,t-1}}\right)^{k_3} \left(\frac{L_{c,i,t-1}}{L_{D,i,t-1}}\right)^{k_4} \times \left(\frac{N_{1,i,t}}{N_{T,i,t}}\right)^{k_5} \left(\frac{N_{2,i,t}}{N_{T,i,t}}\right)^{k_6} \left(\frac{N_{3,i,t}}{N_{T,i,t}}\right)^{k_7} \left(\frac{N_{4,i,t}}{N_{T,i,t}}\right)^{k_8} \left(\frac{N_{5,i,t}}{N_{T,i,t}}\right)^{k_9} \left(\frac{N_{6,i,t}}{N_{T,i,t}}\right)^{k_{10}} \quad (6)$$

$$\frac{L_{b,i,t}}{E_{b,i,t}} = g_0 L_{D,i,t-1}^{g_1} \left(\frac{L_{d,i,t-1}}{L_{D,i,t-1}}\right)^{g_2} \left(\frac{E_{b,i,t}}{E_{T,i,t}}\right)^{g_3} \left(\frac{L_{b,i,t-1}}{L_{D,i,t-1}}\right)^{g_4} \left(\frac{L_{r,i,t-1}}{L_{D,i,t-1}}\right)^{g_5} \quad (7)$$

$$\frac{L_{c,i,t}}{E_{c,i,t}} = p_0 L_{D,i,t}^{p_1} \left(\frac{L_{d,i,t}}{L_{D,i,t}}\right)^{p_2} \left(\frac{E_{c,i,t}}{E_{T,i,t}}\right)^{p_3} \left(\frac{L_{c,i,t}}{L_{D,i,t}}\right)^{p_4} \left(\frac{L_{r,i,t}}{L_{D,i,t}}\right)^{p_5} \quad (8)$$

where L is the area of land in each use (r = residential, D = developable, d = developed, b = basic, c = commercial); E stands for employment by type, as defined above (b = basic, c = commercial, including both retail and service jobs); N represents households by type (totally 6 types); and the k's, g's and p's are estimated parameters.

Travel Demand Model (TDM)

The TDM integrated with the land use model was originally developed by Smart Mobility, Inc. (2003). It represents a rather typical, four-step, aggregate TDM with a couple of added features detailed below. Its main inputs are the roadway network with link capacities and free-flow times and zonal attributes for each traffic analysis zone (TAZ). Zonal attributes include the number of households by type and the number of jobs by type, both of which are provided by the land use model.

As is standard practice, personal trips were segmented by type. A total of ten trip types[3] (including home- and non-home-based, direct and complex, work and non-work) were modeled explicitly, and each TDM module was segmented accordingly. Fixed person-trip rates (per household, per weekday) were used for each of 18 household types (categorized by number of workers, presence of children, and three levels of vehicle availability). Attraction rates for personal trips were determined via linear regression on the numbers of households and employment by type in each zone. Commercial trip model specifications were similar but simpler. Other TDM details can be found in Smart Mobility (2003) or Zhou and Kockelman (2008)

The TDM consists of six modules performed in sequence: auto availability, trip generation, walk/bike mode choice, gravity-style trip distribution, mode choice (among motorized modes), and network assignment. To ensure consistency in input and output travel times, a model feedback mechanism was employed. Some modifications were necessary, and these are described below.

[3] The ten trip types are home-based work direct (HBWD), home-based work complex (HBWC), home-based work strategic (HBWS), home-based non-work retail (HNWR), home-based non-work other (HNWO), non-home-based work (NHBW), non-home-based other (NHBO), K-12 education (ED1), post-secondary/college education (ED2), and airport (AIR) trips.

Since Smart Mobility's trip distribution module only considers zone to zone travel times (but not travel costs), and because travel cost sensitivity is central to tolling scenario tests, a new trip distribution module was calibrated. The new module employed choice models, instead of gravity models, for each trip type, and two explanatory variables: generalized trip cost and zonal attractions computed in trip generation. Here, generalized cost is a simple linear function of travel time and travel cost, where the value of travel time (VOTT) was assumed to be $9/person-hour for work trips and $4.50/person-hour for other trips, consistent with VOTT assumptions used in Smart Mobility's (2003) mode choice module. Operating costs were assumed to be $0.0922/mile, also consistent with Smart Mobility's model. Since model estimation with large numbers of choice alternatives can be difficult (Austin has over 1,000 TAZs), only 50 zone alternatives (chosen at random) plus the chosen alternative were considered in the models' estimation. While not ideal, such methods produce consistent parameter estimates (McFadden 1978).

In addition to modifications in trip distribution, the process of network assignment also was changed, in order to incorporate both time and cost. Similar to Smart Mobility's model, four time-of-day (TOD) periods were considered. However, network assignment was based on the equilibration of generalized path costs instead of just path travel times. Generalized cost is a linear combination of travel time and travel cost, but since all trip types are aggregated for assignment, a single VOTT was used: $6.75/person-hour (the average $9/person-hour and $4.50/person-hour).

DATA DESCRIPTION

This relatively straightforward G-LUM has moderate data requirements: employment and household counts (by type) at the level of TAZs, and land use data (development type areas in each TAZ) at two points of time. Such demographic data is typically available from MPOs, and land use data is becoming more widely available with the advance of GIS tools.

The model system predicts the spatial distributions of six household types (categorized by number of workers [0, 1 and 2+] and presence of children) and three employment categories (basic, retail and service jobs). Table 1 provides the household and employment classifications. Three other employment types (namely Airport, K-12 Education, and Higher Education) were assumed to follow Envision Central Texas (ECT)'s trend scenario[4]. This trend scenario was generated by Fregonese Calthorpe Associates as one of many, during a visioning exercise (Envision Central Texas 2003).

TABLE 1 Employment and Household Classifications

Category	Definition
Type I Household	0-worker household, with at least one child under 18 years of age
Type II Household	1-worker household, with at least one child under 18 years of age
Type III Household	2 or more-worker household, with at least one child under 18 years of age
Type IV Household	0-worker household, with no children
Type V Household	1-worker household, with no children

[4] These three types of employment account for just 4.7% of total jobs in ECT's trend scenario, and they vary significantly over space yet are relatively stable over time (at least for all zones that have non-zero employment counts).

Type VI Household	2 or more-worker household, with no children
Basic Employment	Division A (agriculture, forestry, and fishing) Division B (mining) Division C (construction) Division D (manufacturing) Division E (transportation, communications, electric, gas, and sanitary services) Division F (wholesale trade)
Retail Employment	Division G (retail trade)
Service Employment	Division H (finance, insurance and real estate) Division I (services) Division J (public administration)

The Capital Area Metropolitan Planning Organization (CAMPO) provided year 2000 household counts and 2007 projections at the TAZ level. Total zonal household counts for year 2005 were interpolated using the 2000 and 2007 data, and households by type were calculated using the household type proportions evident in ECT's trend scenario.

High-quality land use data for the entire MSA is quite limited. Only one set of land use data (in year 2005) could be obtained via the Capital Area Council of Governments (CAPCOG). The data was refined using the City of Austin's relatively accurate 2003 land use data base, along with year 2004 orthophotos (to fill in over 3,000 parcels that lacked a land use code). Overlapping parcels were eliminated, and missing parcels were added manually. Obtaining a second historical land use data set to calibrate the models presently is highly impractical. Therefore, land use conditions for the year 2000 were backcast in each TAZ, using 2000 and 2005 household and employment counts (along with the 2005 land use data) and assuming fixed developed land densities (by land use type).

The data used in Smart Mobility's TDM calibration and calibration of the modified trip distribution model came from several sources. The main source was CAMPO's Austin Travel Survey (ATS) of 1996-97. CAMPO provided zone to zone travel time and travel distance estimates for both peak and off-peak periods and automobile and bus modes for year 1997. CAMPO also provided 1997 and 2000 zone population and employment attributes. In model application, two roadway networks were used: one for the base year (1997) and a year 2025 projected network. The 2025 network was taken from Envision Central Texas's trend scenario. For simplicity in model application, the base year network was used to 2010, and each subsequent model year was based on the 2025 network.

This paper is focused on model illustration and general results. For detailed policy-making and predictions, better land use and network estimates are recommended.

MODEL APPLICATION

In this integrated modeling framework, the four model components run in sequence: first EMPLOC, then RESLOC, LUDENSITY, and the TDM. The EMPLOC model output (employment by category by zone) serves as an input to RESLOC. Predicted household and employment levels (by category/type) are LUDENSITY's primary inputs. The TDM was applied last, after allocating households and jobs (and estimating land consumption levels), in order to update travel times between zones and the relative attractiveness of each zone. Figure 1 shows the interactions between these components. Essentially, household and employment distributions and land development processes are believed to lag travel conditions, since changing one's home and work locations is much more difficult than changing the route one takes to work, or the stores at which one shops. Thus, the TDM is consistent with the land use forecasts, but the same-year land use forecasts are lagged responses to the prior period's TDM forecasts.

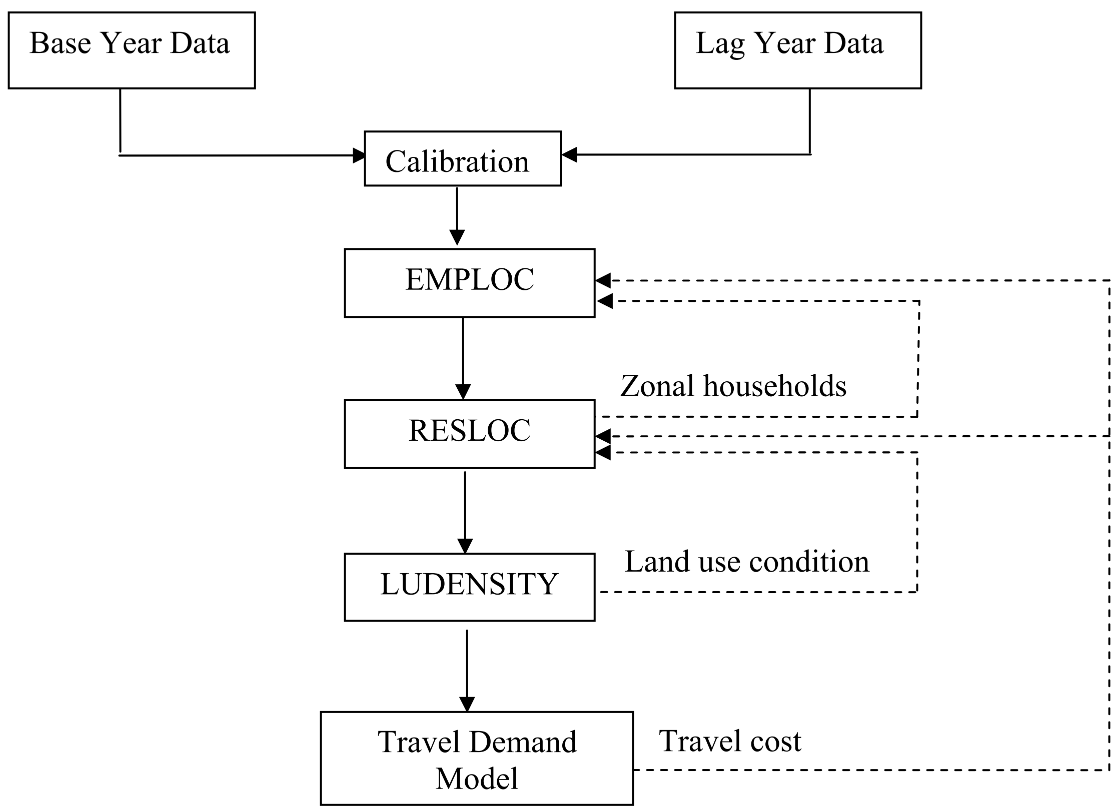

FIGURE 1 Flowchart for G-LUM Modules, in concert with Travel Demand Model

Note: Dashed lines represent one-period (*t*-1) lagged feedback of information. Each period is 5 years.

The models were applied every five years. Regional households in 2030 are assumed to total 931,000 (compared to 476,000 in year 2000) and regional jobs (including basic, retail and service) total 1,348,000 (compared to 614,000 in 2000). Each household type and employment category is assumed to follow an exponential growth pattern, and intermediate totals moderate G-LUM's projections.

Land Use Model Details

MATLAB codes followed TELUM in its treatment of "seeds" and residuals (as described in TELUM's User Manual). In order to ensure reasonable population and job forecasts, certain rules were implemented during model application, and these rules were active in 40% to 80% of

TAZs in a test (one–step) forecast[5]. Those rules are critical to reasonable zone-level projections in many cases[6], and distinguish our code from those of other G-LUMs.

First, households and jobs in each TAZ were not allowed to fall by more than 5% in any (five-year) time interval. Second, growth in these counts was limited by land availability. For each household type, the maximum increase in the ratio of counts between two periods in any given zone was assumed to be the ratio of developable land (i.e., undeveloped and unprotected) to residentially developed land. For each job category, the maximum increase was set as the ratio of developable land to the sum of basic and commercially developed land. Third, in fully developed TAZs, households and jobs were not allowed to increase by more than 5% per time interval[7]. TAZs that violated the first rule were flagged, and then the corresponding number of households or jobs[8] was taken from the un-marked TAZs, in proportion to their original, forecasted counts. Similarly, TAZs that violated the second or the third rules were flagged, and then the "extra" households or jobs were re-allocated to the un-marked TAZs, in proportion to their original counts. This re-allocation process was run iteratively until all TAZs satisfied the three rules.

Like household and employment forecasts, residential, basic, and commercial land were not allowed to fall by more than 5% in any 5-year interval in any zone; and in fully developed TAZs, residential, basic, and commercial lands were not allowed to increase by more than 5% per time interval. In addition, the minimum land per job or household depended on two more factors: land consumptions in the previous period and a pre-specified minimum per household or job. These were assumed to be 500, 250, and 1000 square feet (per household, per basic job, and per commercial job). Moreover, when total forecasted development was expected to require more than the land available in a zone, the forecasted residential, basic, and commercial land totals were proportionally reduced, thus upping densities in each land use category.

Transportation and Land Use Policies

In order to put the integrated system to the test, the land use and transportation effects of three distinctive policies were investigated. These include a business-as-usual (BAU or base) scenario, a road pricing scenario (congestion pricing plus a mileage-based carbon tax), and an urban growth boundary (UGB) scenario (prohibiting new development in presently peripheral, largely undeveloped zones). One underlying assumptions in the policy scenario analyses is that future regional household and employment counts do not vary across scenarios, even though growth could well jump/leapfrog out of the study area, especially under a strict UGB policy.

The ***BAU scenario*** assumes that development trends observed over the five-year calibration will continue, and no new policies are imposed. The ***road pricing scenario*** required special consideration in the TDM system, to ensure marginal cost pricing (of delay) during the trip assignment step. A congestion charge was set to equal these external costs on all freeway

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[5]Roughly 40% of all 1,245 zones violated one or more rules in EMPLOC, about 50% violated rules in RESLOC, and 80% violated rules in the basic land use density equation.

[6] As an example, when using Putman's ITLUP software, North Central Texas Council of Governments (NCTCOG) modelers review and manually modify forecasts every round, to help ensure more reasonable projections (Dankesreiter 2008).

[7] This decision-rule relaxes the second decision-rule for fully developed zones in order to allow for infill in those zones.

[8] This number was simply equal to the deficit needed to ensure the 5% loss rule was not exceeded.

segments in the network. If the travel time on each link is assumed to follow the well-known Bureau of Public Roads (BPR) performance function, average travel time (*t*) is as follows:

$$t = t_f \times \left[1 + \mu\left(\frac{v}{c}\right)^{\varphi}\right] \tag{9}$$

Here, t_f is the link's free-flow travel time, v is demand volume for the link (in vehicles/hour), c is the link's capacity (also in vehicles/hour), and μ and φ are parameters, assumed here to be 0.83 and 5.5, respectively (Martin and McGuckin 1998). The marginal (total travel time) cost of adding another vehicle to the road (MC) is given by the following expression (see, e.g. Small and Verhoef 2007):

$$MC = VOTT \times t_f \times \left[1 + \mu(\varphi + 1)\left(\frac{v}{c}\right)^{\varphi}\right] \tag{10}$$

Here, $VOTT$ is the value of travel time (assumed to be \$6.75/person-hour[9]). When another vehicle enters the roadway, it raises *v* by 1 unit, causing *t* and total system travel time (TSTT) to rise. The added cost endured by others, and thus not perceived by the new traveler, is the difference between the old and new TSTTs. The first-best congestion prices (CPs) can then be estimated as follows:

$$CP_s = VOTT \times t_f \times \mu\varphi\left(\frac{v}{c}\right)^{\varphi} \tag{11}$$

The congestion toll varies across links and times of day because of changes in volume-to-capacity ratios (and thus the marginal delay imposed by additional link users). The average values for Austin's application are 1.5 to 3.2¢/mile during peak hours.

The carbon tax is assumed to be 4.55 cents/mile on *all links* in the network, calculated as follows:

$$CT = \frac{26\, lb/gal}{20\, mi/gal} \times \frac{\$70/ton}{2000 lb/ton} \tag{12}$$

Equation (12) assumes that every gallon of gasoline sold at the pump is responsible for the emission of 26 pounds of carbon dioxide (EPA 2007), the cost of removing carbon from the atmosphere (or simply avoiding its production) is \$70/ton[10], and average fuel economy is 20 miles per gallon of gasoline.

Since tolling equipment (such as overhead gantries, variable message signs, and communications technology for link use and customer accounts) is pricey (see, e.g., Gulipalli and Kockelman [2008]), only links that are classified as freeways (by CAMPO) were assessed a congestion toll in the road pricing scenario.

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[9] VOTTs are \$9/hour for work and airport trips and \$4.5/hour for non-work trips in the destination and mode choice models. The average of the two was used in setting congestion charges. In theory, the true marginal delay is a function of who is on the link at the time a marginal user is added.

[10] Using different discount rates, risk values and distributions of carbon savings, Tol (1999) estimated a wide range of possible carbon emissions – from just \$1 or \$2/ton to over \$300/ton. \$70 per ton corresponds to Tol's (1999) median cost estimate with a discount rate of 3%. Based on recent trends, estimates lie closer to \$50 per ton (see e.g., Fischer et al. 2007, U.S. Environmental Protection Agency 2008, CRAI 2008).

The ***urban growth boundary (UGB) scenario*** restricted all types of new development to a pre-defined set of largely contiguous zones, centered on existing population centers. Zones outside of this "boundary" were not permitted any new residential, basic or commercial development. Developable zones were defined as TAZs having 2 or more job-equivalents[11] per acre, and any TAZs touching their boundaries (essentially to ensure adequate lands for 25 more years of Austin's development). The bounded area accounts for 14.8% of all developable land in the region (or 12.7% of total acreage) Figure 2 shows the set of zones lying within and outside the UGB used in this study.

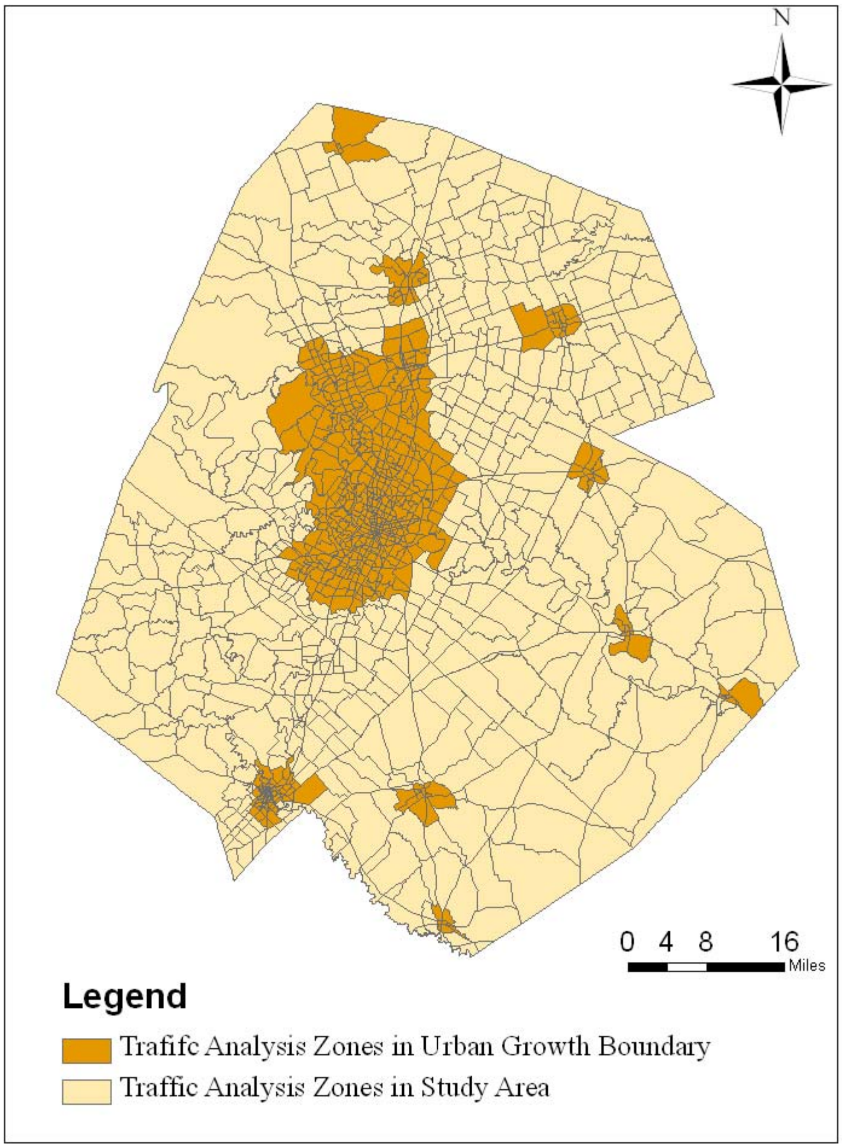

FIGURE 2 Urban Growth Boundary Map of Austin-Round Rock MSA

[11] One household is counted as 0.7143 jobs, because the regional employment rate is 1.4 jobs per household.

MODEL RESULTS

This section discusses the results of model calibration, as well as the results of model application for the three policy scenarios. Variables like vehicle-miles traveled (VMT), traffic flows, volume-to-capacity ratios, speeds, and downtown accessibility indices (to households and employment) are summarized.

Model Calibration and Results

Due to the nonlinearities embedded in the G-LUM model specification, non-linear least squares (NLLS) technique was used (as described in Greene [2000]). Putman (1983) found that least-squares techniques tend to seek the optimum over a relatively flat surface, while maximum likelihood estimation (MLE) may enjoy a steeper surface (in his experiments with only one unknown parameter and 25 or fewer zones). However, the optimization surface for such gravity-based land use models is highly irregular and non-convex; starting values have significant impacts on the optimization results, requiring multiple searches with different starting values[12]. This can compromise any advantage of MLE methods. NLLS techniques are easier to understand and implement, and so were used here, for model parameter estimation. Table 2 provides the model's 110 parameter estimates and their corresponding t-statistics.

The model calibration results reveal that past counts of households and jobs ($\Delta t = 5$ years) are strong predictors of current counts of all household types, as well as basic and retail employment, because the estimated η and λ values are close to zero (as shown in Table 2); so the estimated parameter of (and reliance on) historical counts are close to one. In general, rising travel times reduce a zone's relative attractiveness for new residential development, as shown by the negative signs of estimated α and β values in Table 2. However, for job distributions, the role of travel time, and thus a zone's regional accessibility appears mixed. Moreover, many coefficients in the attractiveness function (Equation 3) for household allocations are statistically insignificant, especially the ones in the following multiplicative function:

$$\prod_{n'}\left[\left(1+\frac{N_{i,t-1}^{n'}}{\sum_{n} N_{i,t-1}^{n}}\right)^{b_{n'}^{n}}\right] \tag{13}$$

This suggests the possibility of over-specification of the household attractiveness function. However, in order to maintain a model specification most similar to TELUM's and ITLUP's, the 62 statistically insignificant (out of 110) parameters were retained.

The amount of developable land in each zone is a valuable predictor of residential, basic, and commercial development in the LUDENSITY model, with a high level of statistical significance. The ratios of developed, basic, and commercial uses to developable land are more statistically significant, as compared to the ratios of households by type to total household counts in predicting residential uses. The ratio of residential use to developable land is statistically insignificant in prediction of basic and commercial development. These indicate that corresponding land use conditions in prior time period can better explain current land development, as compared to other land use types.

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[12] 20 starting points were used here.

TABLE 2 G-LUM Parameter Estimates

RESLOC						
	η	α	β	q	r	s
Type I Households	0.0317 (2.94*)	-2.07 (-4.32*)	-0.0232 (-0.55)	1.20 (1.97*)	4.82 (0.83)	0.566 (5.18*)
Type II Households	0.0665 (12.34*)	-1.19 (-3.07*)	-0.0396 (-1.81*)	0.530 (4.45*)	0.371 (0.42)	0.0342 (1.10)
Type III Households	0.0747 (11.33*)	-0.772 (-1.55)	-0.0509 (-1.93*)	0.622 (4.87*)	1.54 (1.78*)	0.0103 (0.25)
Type IV Households	0.0264 (5.83*)	2.73 (1.08)	-0.2281 (-1.89*)	0.954 (2.10*)	0.631 (0.14)	0.312 (2.55*)
Type V Households	0.0467 (11.16*)	51.14 (1.20)	-7.92 (-1.19)	0.724 (2.67*)	2.43 (1.10)	0.0227 (0.57)
Type VI Households	0.0615 (10.27*)	-1.14 (-2.13*)	-0.0640 (-2.02*)	0.611 (3.39*)	-0.882 (-0.64)	0.157 (1.71*)
	b_1^n	b_2^n	b_3^n	b_4^n	b_5^n	b_6^n
Type I Households	80.02 (1.89*)	-1.69 (-0.05)	-11.92 (-0.48)	0.234 (0.01)	-8.18 (-0.27)	0.0233 (0.00)
Type II Households	6.29 (1.18)	6.41 (1.16)	9.45 (1.67*)	0.345 (0.07)	4.32 (0.75)	0.962 (0.19)
Type III Households	4.13 (0.60)	-3.13 (-0.44)	8.98 (1.02)	-2.10 (-0.26)	0.0218 (0.00)	-2.15 (-0.29)
Type IV Households	40.09 (1.21)	-1.31 (-0.03)	-11.08 (-0.34)	6.32 (0.15)	-9.87 (-0.26)	-0.317 (-0.01)
Type V Households	2.12 (0.21)	-1.08 (-0.15)	-2.33 (-0.28)	-9.49 (-1.37)	2.35 (0.24)	-3.68 (-0.44)
Type VI Households	20.20 (1.51)	-11.16 (-1.84*)	-4.76 (-0.73)	-9.30 (-1.52)	-7.24 (-1.08)	-3.59 (-0.48)
EMPLOC						
	λ	ω	ρ	a	b	
Basic Employment	0.00713 (4.13*)	-5.34 (0.00)	0.876 (0.01)	10.56 (0.05)	-16.76 (-0.05)	
Retail Employment	0.0836 (7.72*)	0.517 (0.15)	-0.253 (-0.79)	0.126 (0.81)	0.611 (3.15*)	
Service Employment	0.361 (3.68*)	2.33 (1.89*)	-0.126 (-3.81*)	0.600 (7.39*)	-0.0322 (-0.33)	
LUDENSITY						
Residential Uses	k_0	k_1	k_2	k_3	k_4	
	1.34 (0.31)	0.930 (14.57*)	0.279 (2.41*)	-0.0111 (-1.45)	-0.0481 (-2.63*)	
	k_5	k_6	k_7	k_8	k_9	k_{10}
	0.423 (1.46)	0.00287 (0.01)	1.43 (2.85*)	0.00388 (0.01)	0.218 (0.49)	3.27 (3.87*)
Basic Uses	g_0	g_1	g_2	g_3	g_4	g_5
	0.000249 (3.32*)	3.04 (20.67*)	-1.06 (-3.35*)	-2.38 (-5.35*)	2.82 (20.50*)	-0.00771 (-0.86)
Commercial Uses	p_0	p_1	p_2	p_3	p_4	p_5
	0.000580 (3.51*)	1.95 (18.29*)	-1.07 (-4.52*)	-1.05 (-7.17*)	1.75 (11.06*)	-0.0244 (-1.01)

Notes: Numbers in parentheses are t-statistics. Asterisks (*) are for statistically significant variables.

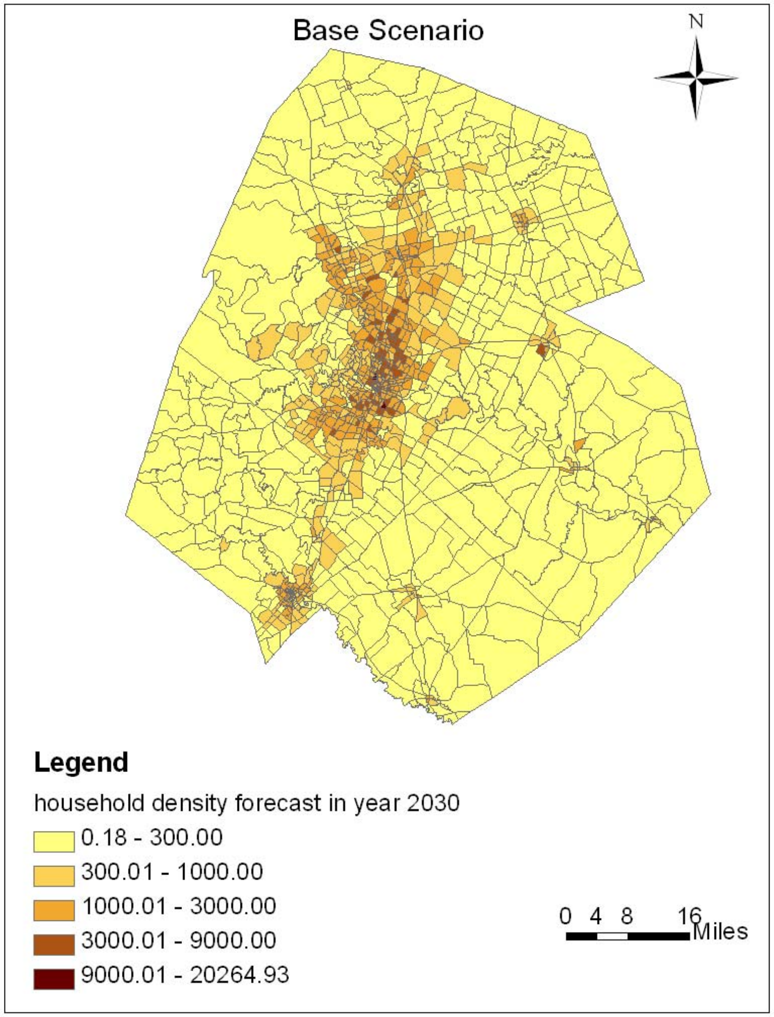
Household and Employment Distributions

Figure 3a presents the forecasted distribution of households and jobs at the TAZ level in year 2030, assuming ***business as usual*** behavior and policies. As shown in these maps, households and employment tend to remain concentrated in the urbanized zones and along regional freeways.

The household and employment density forecasts when implementing ***road pricing*** (congestion pricing on freeways plus a carbon tax on all roads) are shown in Figure 3b. The distribution patterns are similar to the results of the BAU scenario, using the same legend thresholds. This suggests that the road pricing policy will not alter the location choices of households and firms in a significant way. Such lack of responsiveness is suspected to come from two important sources: First, added travel costs (4.55¢/mile for added fuel costs and another 1.5 to 3.2¢/mile for average congestion tolls during peak hours) are just 10 percent of underlying car ownership and use costs (FHWA 2001), except in highly congested corridors at peak times of day when demand-based tolls sometimes reach $1/mile. Thus, locators may consider such cost changes to be rather negligible. Second, and more critical for future scenario testing: the gravity model formulation is relatively insensitive to constant shifts in travel costs (Equations 1 and 4's c_{ijt}). This seems fundamentally unrealistic, since a lack of good regional access (e.g., all trips suddenly incur a fixed toll of $10) should result in more clustering at central and other nodal locations. Of course, if speeds are all reduced on the network or new tolls apply per mile traveled, there will be more of a scaled (rather than constant) shift in travel costs and thus more centrally located zones will enjoy improvements in their *relative* attractiveness, but such relative movements may be insufficient to generate new preference patterns accompanying such network conditions. A new paradigm/LUM specification is needed, to allow for more appropriate response opportunities.

A third reason for such insensitivity is that over 90 percent of next-period (Δt = 5 years) predictions are simply the lagged count value in each zone (except for basic employment), resulting in much "friction" in the system. While not unreasonable for many scenarios, more dramatic scenarios (e.g., those with strong incentives for household-move decisions) may not keep pace with actual location changes, at least not in the short term.

Figure 3c shows household and employment density forecasts for the ***UGB*** scenario. As compared to the base (2005) conditions, the ***BAU*** and ***road pricing*** scenarios predict that some TAZs in Austin's core will lose households over the next 25 years, while some TAZs at the city's periphery, especially in the northern part, gain households. Most TAZs were predicted to gain jobs between 2005 and 2030, with a few exceptions for TAZs in downtown and the northern part of the City of Austin. When implementing the ***UGB policy***, household and employment (basic, retail, and service) growth were predicted to concentrate within the predefined boundaries, as defined by the policy, though a few TAZs within the UGB were forecasted to lose households and/or jobs.



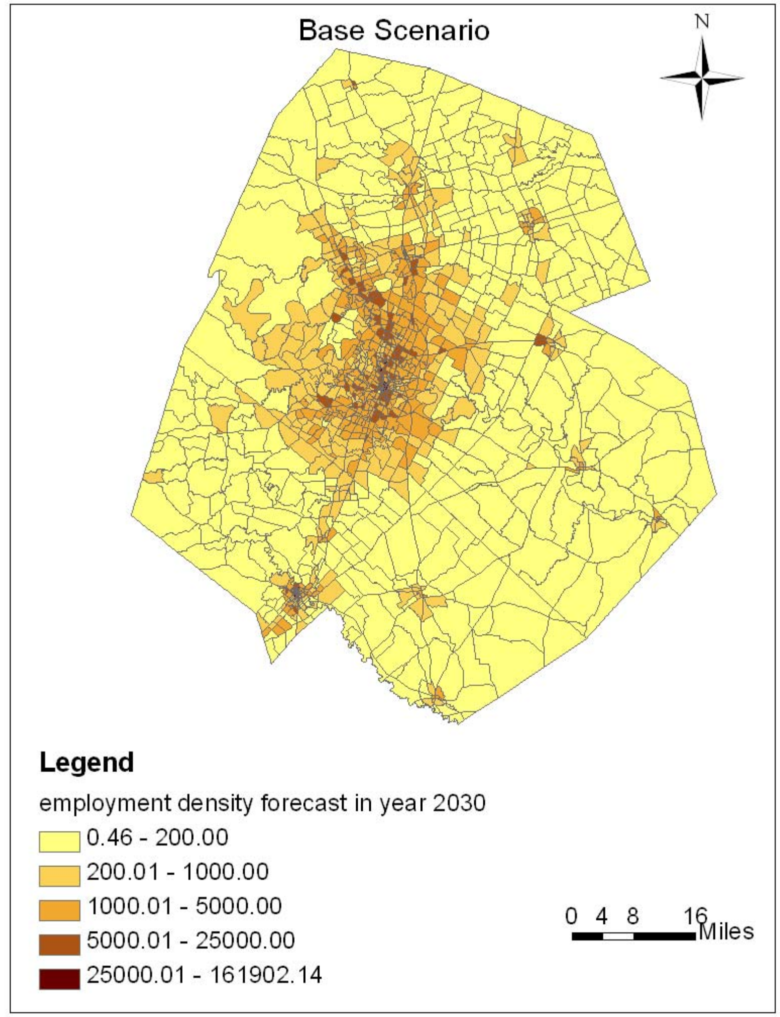


FIGURE 3a Household and Employment Density Predictions in Year 2030 for Scenario A (Business-As-Usual)

Note: Unit is count (of households and jobs) per square mile.

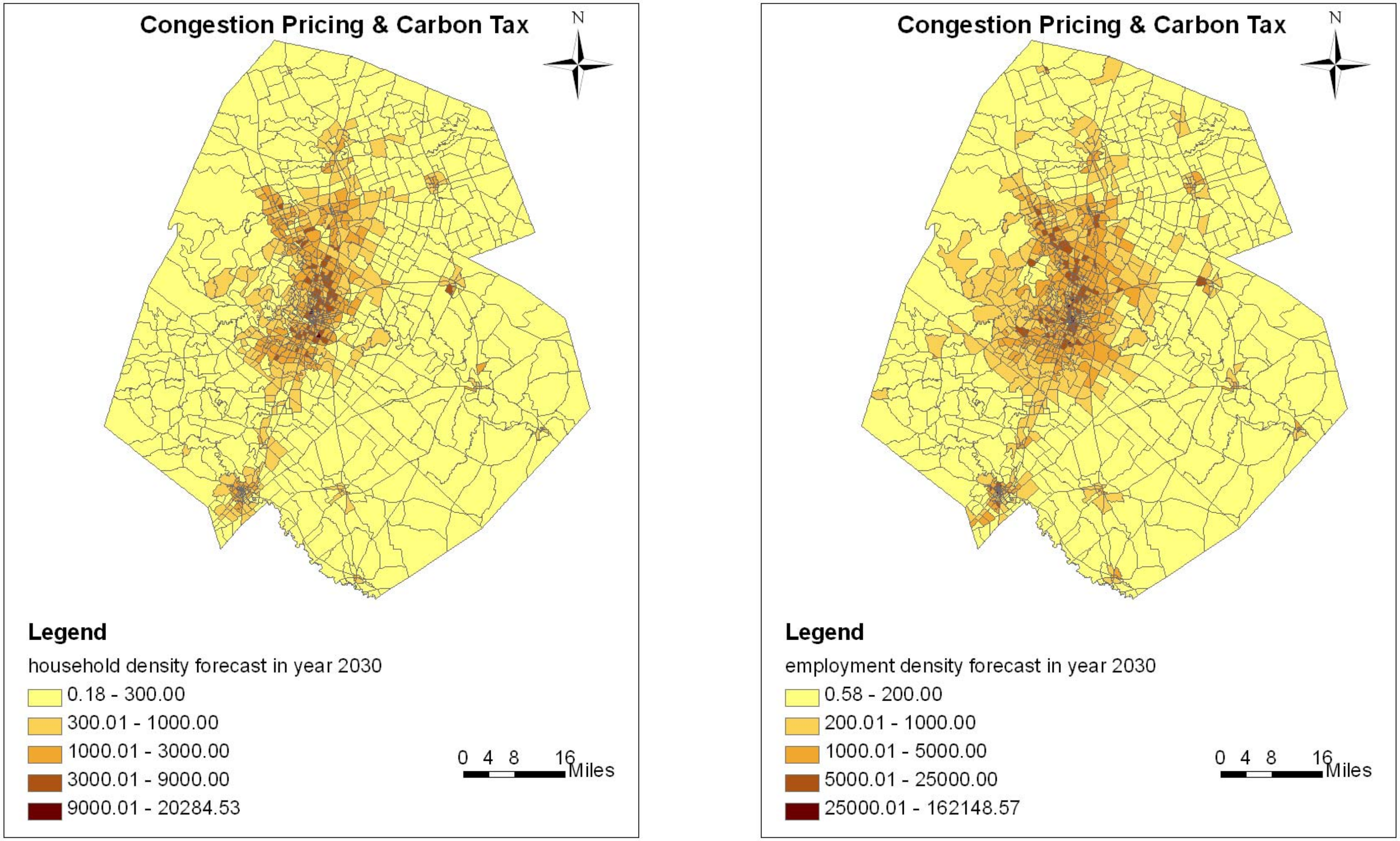


FIGURE 3b Household and Employment Density Predictions in Year 2030 for Scenario B (Road Pricing and Carbon Tax)

Note: Unit is count (of households and jobs) per square mile.

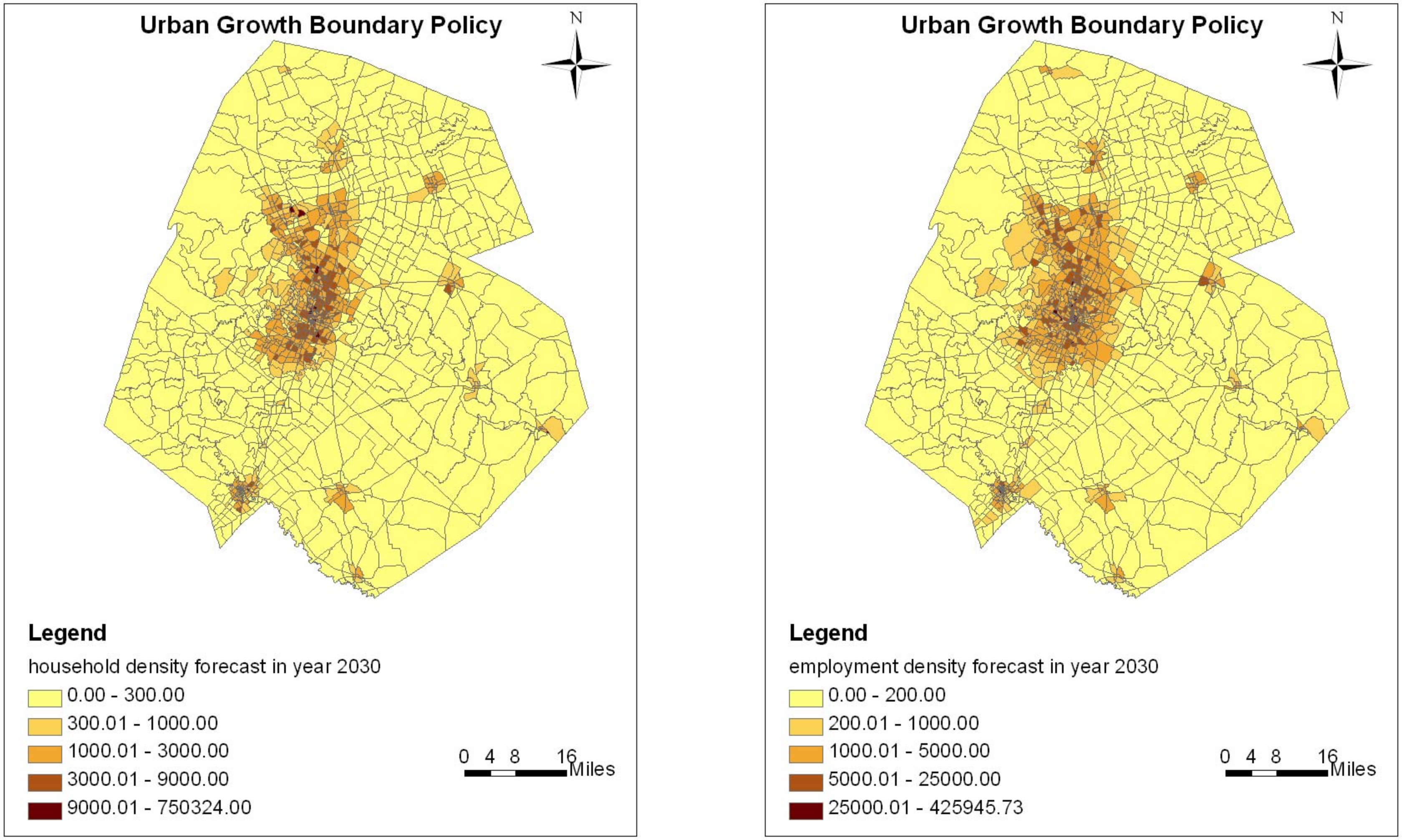


FIGURE 3c Household and Employment Density Predictions in Year 2030 for Scenario C (Urban Growth Boundary)

Note: Unit is count (of households and jobs) per square mile.

In order to quantify the differences between the three scenarios with a single measure, a simplistic accessibility index (AI) for the region's CBD was developed as follows:

$$AI = \sum_i \frac{Count_i}{Distance_i} \qquad (14)$$

where $Count_i$ is the count of total households or total jobs in zone i and $Distance_i$ is the inter-centroidal Euclidean distance (in miles) from TAZ i to Austin's core TAZ (housing Texas's capitol). This simple AI was calculated for both jobs and households for each scenario. The spatial distribution of households and employment under the ***UGB policy*** exhibit the highest AI values (3.7 and 69.3 million, respectively), indicating that the UGB policy generated the most centralized development pattern. As expected, the AI values for the ***BAU*** and ***road pricing*** scenarios are similar (1.8 versus 1.5 million for households and 62.9 versus 63.2 million for employment under both scenarios). It seems that road pricing may not affect location-specific accessibilities enough to prompt regional centralization of land uses, but, as discussed below, it is forecasted to have a strong impact on travel.

Results of the Travel Demand Models

Of course, the TDM results are of great interest as well. VMT estimates, volume-to-capacity ratios, and mode splits for all scenarios closely relate to congestion levels as well as mobile-source emissions. Results are listed in Table 3. VMT values for 2030 (by time-of-day) across the three scenarios suggest that the road pricing and UGB policies are rather effective in reducing VMT. These two policy scenarios were estimated to reduce regional VMT, relative to the BAU case by 16.0% and 17.2%, respectively, or 14.5 or 15.7 VMT per household per day. As compared to the base year 2005 (when the forecasting starts), the BAU scenario anticipates a 98.7% increase in regional VMT (compatible with 95.6% and 119.5% increases in households and jobs over the same 25-year period), versus just 67.0% and 64.5% for the road pricing and UGB policies, respectively.

TABLE 3 Vehicle Miles Traveled (VMT) and Intra-Regional Trips Predicted for Year 2030 across Scenarios

	Base Scenario	**Road Pricing**	**Urban Growth Boundary**
Vehicle Miles Traveled ($x10^6$/weekday)			
AM (6:30 – 9am)	17.01	14.64	14.21
OP (9 am – 3 pm & 7 – 9 pm)	6.46	5.47	5.34
PM (3 – 7 pm)	27.18	22.82	22.49
MID (9 pm – 6:30 am)	34.15	28.33	28.19
Total	84.79	71.25	70.22
Person-Trips by Type ($x10^6$/weekday)			
Personal	11.25	11.25	10.70
Commercial	0.64	0.64	0.62
Total	11.89	11.89	11.32

Person-Trips by Mode (x10^6/weekday)			
Walk/Bike	0.37	0.37	0.47
Transit	0.90	1.03	0.97
Auto	9.97	9.85	9.27
Total	11.25	11.25	10.70
VMT-weighted Average Speeds (miles/hour)			
AM (6:30 – 9am)	47.3	52.0	49.3
PM (3 – 7 pm)	52.2	55.1	52.8
Peak-hour Average	50.3	53.9	51.4
VMT-weighted Average Volume-to-Capacity Ratios			
AM (6:30 – 9am)	0.692	0.576	0.656
PM (3 – 7 pm)	0.592	0.475	0.577
Peak-hour Average	0.631	0.515	0.608

Predictions of total intra-regional trips suggest that the BAU and road pricing policies generate similar numbers of personal and commercial trips (due to similar land use pattern predictions), while the UGB policy reduces total trip-making by 4.8%, or 0.57 million trips per weekday (due to the fact that trip generation rates vary by location within the region, and the UGB scenario results in a much denser and centralized distribution of households and jobs). Comparisons of the VMT and trip numbers across scenarios suggest that VMT reductions under the road pricing policy come mostly from shorter trips, while VMT reduction under the UGB policy comes both from shorter trips and fewer trips.

Mode share results (walk/bike, transit, and auto) indicate that the road pricing and UGB policies promote transit usage while reducing the number of automobile trips, but not by much. This suggests that even strict policies may not break Austinites' reliance on the automobile. The UGB scenario enjoys the highest number of walk and bike trips, bettering the other two policies by 27 percent. This is not surprising since the choice of walk and bike modes in the TDM depends on the number of zones with good mix of households and jobs, and such zones are more prevalent in the UGB scenario.

Table 3 also provides the VMT-weighted average speeds and VMT-weighted average volume-to-capacity ratios for each of the three policy scenarios. The road pricing policy is predicted to be the most effective at increasing average speeds across the region's network (by 7.03% or 3.54 mile/hour) and reducing the volume-to-capacity ratios (by 18.4% or 0.116).

LIMITATIONS OF GRAVITY LAND USE MODELS

As one of the most widely applied land use techniques in the world, gravity-based allocation methods enjoy a simple model structure, moderate data demands, and relatively straightforward estimation. Such benefits can be critical for agencies and modelers that do not have the resources on hand for more sophisticated modeling approaches. Clear limitations in opportunities for policy analysis (see, e.g., Lemp et al. 2008) and poor performance with relatively disaggregate zonal systems and/or lightly developed zones (PBQD 1999) are noted issues. This study adds to the list of potential problems and offered some suggestions for model improvement.

In the example applications pursued here, reasonable forecasts emerged only after imposing a variety of hard-coded rules. These rules "dampen" the extreme outputs that emerge in 40% to 80% of all TAZs over the model's initial five-year time step. While forecasts then appeared relatively reasonable (largely based on visual inspection), a few downtown zones (in both Austin and San Marcos) were predicted to have unbelievably high population and job densities by the year 2030, especially under the UGB scenario. This suggests that the G-LUM calibrated here and probably many others, even with a series of constraints prohibiting excessive new development in fully developed zones and depopulation of other zones, may not survive close scrutiny. As done in places like Dallas-Ft. Worth, manual adjustments of results in each period may be needed (Dankesreiter 2008).

Another option is to make the household and job allocation models (referred to as RESLOC and EMPLOC here) more sensitive to LUDENSITY model forecasts. Under the current specification, LUDENSITY does not provide direct feedback to EMPLOC, and enters RESLOC only via three land use variables. LUDENSITY's land availability forecasts should impact the maximum number of new households and jobs that can be allocated to a zone.

In general, the LUDENSITY formulation (based on Putman's [1991] LANCON specification) does not make great sense, and tends to generate unreasonable average land consumption values for households and jobs (as compared to base and prior year land conditions in each zone). This sub-model may be dramatically improved by adding a lagged density term, allowing it to "pivot off" of recent land use densities in each zone, rather than relying on model averages (which presently causes it to ignore current zone densities).

Yet another issue is that many RESLOC coefficients are statistically insignificant, especially those involving lagged shares of households. The RESLOC equation probably suffers over-specification, and could be simplified by defining a single indicator of household balance (across types).

Of course, existing gravity-based LUMs are aggregate in nature and therefore limited by level of detail. For example, land use information at the level of neighborhood zones is generally too coarse for detailed analysis of land cover change and associated biogenic emissions estimation. Such models also are totally unresponsive to certain policies, such as land taxation and subsidies, adequate public facilities ordinances (APFOs), and many styles of zoning. Modelers need to be fully aware of these limitations before seeking to develop and then apply such models. If not, they may be sorely disappointed late in the modeling process.

CONCLUSIONS

This study generated households and employment forecasts by calibrating and applying a gravity-based land use model, based on Steven Putman's (1983, 1991) ITLUP specification. During the course of this work, three important limitations emerged: a great need for rules that moderate model estimates (to ensure reasonable forecasts), clear deficiencies in specification of the land consumption/density model, and over-specification of the residential allocation model. Modeling modifications suggested here provide directions for improvement, and may allow gravity-based LUMs to serve as a reasonable tool for small- to mid-size MPOs.

Results of the rule-constrained model suggest that business-as-usual and road-pricing scenarios will result in similar household and employment distributions (due to a basic flaw in the gravity specification, where travel costs enter the exponential function linearly), but rather different travel behaviors, as characterized by daily VMT, average speed, and network volume-to-capacity ratios. As required (by definition), the UGB policy is predicted to allocate all new development (households and basic, retail, and service jobs) within developable zones. Comparisons between year-2005 land use patterns and year-2030 estimates suggest that many core TAZs will lose households over the next 25 years, while some TAZs at Austin's periphery may attract households. A few central TAZs are forecasted to lose jobs, but this trend is less obvious, as compared to household allocations. Employment opportunities remain heavily concentrated in the region's core under each policy scenario.

The road pricing and UGB policies appear to be powerful tools for VMT reductions. As compared to the base-case, these two policy scenarios were estimated to reduce regional VMT by 16.0% and 17.2%, respectively. The base-case and road pricing scenarios generate similar levels of personal and commercial trips, while the UGB policy generates fewer of both. This suggests that the VMT reduction of the road pricing policy mostly comes from shorter trips, while VMT reductions under the UGB policy come from shorter trips as well as fewer trips.

Volume-weighted averages of speeds and VMT-weighted volume-to-capacity ratios provide single-value performance measures for the entire study area. Policy comparisons suggest that the road pricing policy will increase average speeds by 3.54 mi/hour (or 7.03%) and reduce the region's overall volume-to-capacity ratios by 18.4% (or 0.116), being an effective policy in increasing speed and alleviating congestion – but not offer much, if anything, in the way of altered land use patterns. It appears that common G-LUM specifications are rather insensitive to overall directed changes in travel costs, rendering the TDM feedback to LUM less useful. A closer eye towards model specification can help avoid some of this.

In general, such gravity-based methods for LUM are relatively straightforward, requiring reasonable inputs of data and time for calibration and application. Nevertheless, their accuracy is questionable, and model specification and empirical results must be reviewed carefully, using local knowledge and expert opinion. Such model behavior can then be restrained, via code (internally) or manual adjustment (at each time step). Our restricted G-LUM specification appears to highlight interesting directions for land use patterns in Austin while facilitating long-term traffic forecasts. Rapidly growing regions like Austin may head in any number of directions, depending on local land use and transportation policies. Such models remain of some use in anticipating the general direction and potential magnitude of various transportation policy and investment decisions, along with some styles of land use policy. They allow for transportation system feedback to land use decisions (though such linkages may be weak, as observed in the Austin road pricing scenario), offer a reproducible construct, and facilitate rapid estimation of results for multiple scenarios of interest. We hope public provision of such LUM code[13] will lead to greater use and improvement in modeling approaches of all types.

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[13] The open-source code for mode calibration and application is available at http://www.ce.utexas.edu/prof/kockelman/G-LUM_Website/homepage.htm.

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LIST OF TABLES AND FIGURES