Testing an Integrated Land Use and Transportation Modeling Framework for a Small Metropolitan Area

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This paper describes the implementation of a land use and transportation modeling framework developed for Chittenden County, Vermont, to test for differences in modeled output when employing a dynamically linked travel demand model (TDM) versus an assumption of static regional accessibilities over time. With the use of the land use model UrbanSim, two versions of a 40-year simulation for the county, one with a TDM and one without, were compared. In the first version, UrbanSim was integrated with the TransCAD four-step TDM; this allowed regional accessibilities to be recalculated at regularly scheduled intervals. In the second version, TransCAD was used to compute year 2000 accessibilities; these values were held constant for the duration of the model run. The results indicated some significant differences in the modeled outputs. In particular, although centrally located traffic analysis zones (TAZs) reveal relatively little difference between the two models, the differential within peripheral TAZs is both more pronounced and more heterogeneous. The pattern displayed suggests that some peripheral TAZs have higher modeled development with a TDM because the TDM accounts for the increased proximity of destinations, thereby making them amenable to development. Meanwhile, some peripheral TAZs have lower modeled development with a TDM because they already have good accessibility (e.g., access via Interstate), but the model without the TDM does not account for increased congestion.

Although there are strong interdependencies between land use and transportation, land use planning and transportation planning have traditionally been compartmentalized and separated into different agencies, such that planning for one frequently did not adequately address the other (*1*, *2*). These interdependencies, and the need to plan for them in an integrated fashion, have increasingly been recognized by many researchers (*2*–*6*) as well as by FHWA (*7*). In fact, under the Intermodal Surface Transportation Efficiency Act of 1991 and to a lesser extent the Transportation Equity Act for the 21st Century of 1997, state or regional transportation agencies have been encouraged to model the effect of transportation infrastructure investment on land use patterns, and to consider the consistency of transportation plans and programs with provisions of land use plans.

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Other federal programs have attempted to encourage integrated land use and transportation modeling, including the Travel Model Improvement Program (1992) and the Transportation and Community and System Preservation Pilot program (1999). In response to this need, there has been increasing interest in and focus on the use of simulation models that dynamically integrate land use and transportation (*8*).

Land use simulation models attempt to predict the future densities, types, and distributions of urbanization patterns for a region. Miller (*8*) suggests four components as critical to the integration of land use and transportation models: land development, location choice for households and employers, travel and trip-making behavior, and auto ownership. He also suggests four core drivers that should be accounted for in modeling urban systems: demographic change, regional economic evolution (industry type, size, distribution), government policies (zoning, taxation, etc.), and all modes of the transportation system.

UrbanSim (*9*–*11*) is a land use model under development at the University of Washington's Department of Urban Design and Planning. A recent review of land use models found UrbanSim to be one of the best because of its ability to be integrated with a number of different proprietary and open-source transportation models (*12*), as well as its ability to perform scenario analysis to address long-range planning issues. UrbanSim simulates land use change for a designated area by spatially allocating household and employment locations based on externally derived forecasts of population and employment growth. It operates in an iterative fashion, in which supply–demand imbalances are addressed incrementally over multiple time steps. The model is composed of a suite of submodels that simulate economic and demographic transitions, household and employment location and mobility, land rent and real estate development (location, size, and type), and accessibility of households to community services and cultural amenities (Figure 1). Because it is dynamic, UrbanSim can take factors as endogenous that other models take as exogenous, such as the location of development that occurs after the base year and changes in the price of land and buildings. Exogenous inputs to the model include macroeconomic indicators of employment conditions and real estate transactions, outputs from an independent travel demand model (TDM), and user-specified conditions such as land use policies or scheduled events (typically large-scale development events).

Generally, the transportation model is run for the initial time step to establish baseline accessibilities and then at a user-specified interval thereafter to update those accessibilities in response to changing land use and congestion factors. Because the timing and location of development events depend in part on measures of accessibility, updating these values in the model database makes the interaction of land use and transportation dynamic. The land use change model components are run on an annual time step simulating partial equilibration as

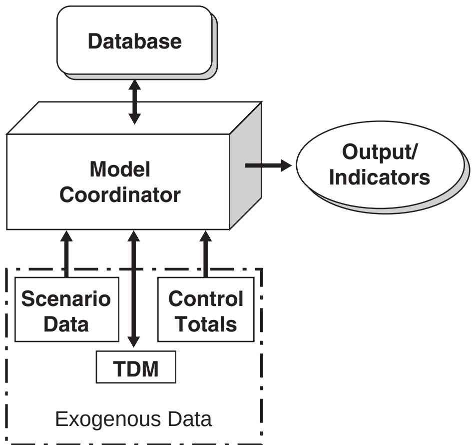


FIGURE 1 UrbanSim model architecture.

actors adjust to the rate of change of fluxes within the economic system or the housing market. Additionally, because each model component is based on a statistically estimated equation, the selection of explanatory variables can be influenced by the availability of specific data sets and tailored to represent unique or distinctive local features that influence transportation and development decisions.

RESEARCH OBJECTIVES

The primary objective of this investigation is to test the effects of including versus excluding an endogenous TDM as one component of a combined land use–transportation modeling framework. The intent is to examine whether the added complexity of endogenous accessibility modeling significantly affects predicted land use change. That is, do indicators of predicted land use change differ depending on whether accessibilities are updated to reflect changing land use? This question is important for several research and policy based reasons. From a research standpoint, the authors are interested in understanding and quantifying uncertainty propagation over the course of a model run. To do this, the results of hundreds of model runs are needed. Considering that approximately 70% of a full model run consists of the TDM, there is the potential to save a significant amount of time generating a sufficient set of outputs. Also considered is the impact on municipalities or regions that are not large enough to warrant the creation of a metropolitan planning organization, yet still face many of the growing pains of larger communities and metropolitan areas. If a TDM is not necessary to produce accurate land use change projections, there is the potential to save (already limited) staff time and taxpayer financing for more pressing needs. Additionally, if the results are indeed shown to be different, they would lead researchers to question the location, timing, and extent of development generated by modeling land use only. Such a question may be critical for understanding long-term environmental impacts from land use change, especially as they relate to the relationships among land conversion (from nonurban to urban uses) and changes in land cover, water quality, and habitat fragmentation.

As population and employment grow, the amount of total travel should also grow. However, what is less clear is whether that growth in demand for road space would actually increase travel time to the extent that resulting land use patterns would be affected. If land use change causes significant congestion, it is expected that future land use development would be responsive by locating in areas with lower congestion, better overall accessibility, or both. If the results of the two models displayed relatively little difference, this result would suggest that the added cost, overhead, and complexity of dynamically integrating the travel model (or considering the effects of congestion at all) does not cause the system to reach any critical thresholds that would in turn affect development patterns. Such a case would suggest that for a regional system with characteristics similar to Chittenden County, the effort and expenses of considering regional accessibilities as endogenous may not be necessary to predict land use.

STUDY SITE

Chittenden County, Vermont (Figure 2), was selected as the study site for this research for several reasons. First, as a metropolitan area of relatively low population (146,671 according to the 2000 U.S. census of the population), the geography of the county (covering a total area of 540 mi^2) is extremely tractable from a modeling standpoint. Second, the county is relatively isolated (3 h from the nearest major American city), which means that it can be modeled as a closed economic system, a frequently held but often violated assumption of land use modeling. Third, the county is an excellent place to study patterns of urbanization because it has diverse possible future trajectories because of the large, relatively undeveloped (but actively developing) areas surrounding the metropolitan area of Burlington (Vermont's largest city), a continued transition away from manufacturing toward a service-oriented economy, and a populace that is highly dependent on automobiles for transportation. Additionally, the Chittenden County Metropolitan Planning Organization (CCMPO) has collaborated with a consultant for several years to develop and implement a TDM for Chittenden County using TransCAD. Finally, members of the research team have recently been awarded one of two U.S. Department of Transportation (USDOT) grants to implement the TRANSIMS model and dynamically link it to UrbanSim.

DATA DEVELOPMENT

Spatial data processing and analysis were performed using ESRI's ArcGIS 9.2, and tabular data were processed and assembled using Microsoft Access. The compiled base year data set was passed to MySQL for running the model. Custom software tools (e.g., SQL scripts, ArcGIS Model Builder models) have been developed to facilitate data transfer among the different platforms to improve the work flow and ensure consistency in data handling. The data development stage for the Chittenden County model was complicated by two primary factors: (*a*) land use decisions are made at the town level in Vermont, and as a result, a majority of the parcel-level data sets for the model come from the 17 individual towns within the county, oftentimes in different formats representing variable levels of completeness, and (*b*) a majority of the essential data was stored as paper records.

In cases in which data do not exist, the gaps were filled by imputing values based on adjacent (or nearby) observations. For example, one essential piece of data required by the model is the year that structures were built. Of the 17 towns in Chittenden County, less than five had this information stored digitally. Several of the remaining towns (that contain a high proportion of the county's total population and employment) stored their property records in paper files, and

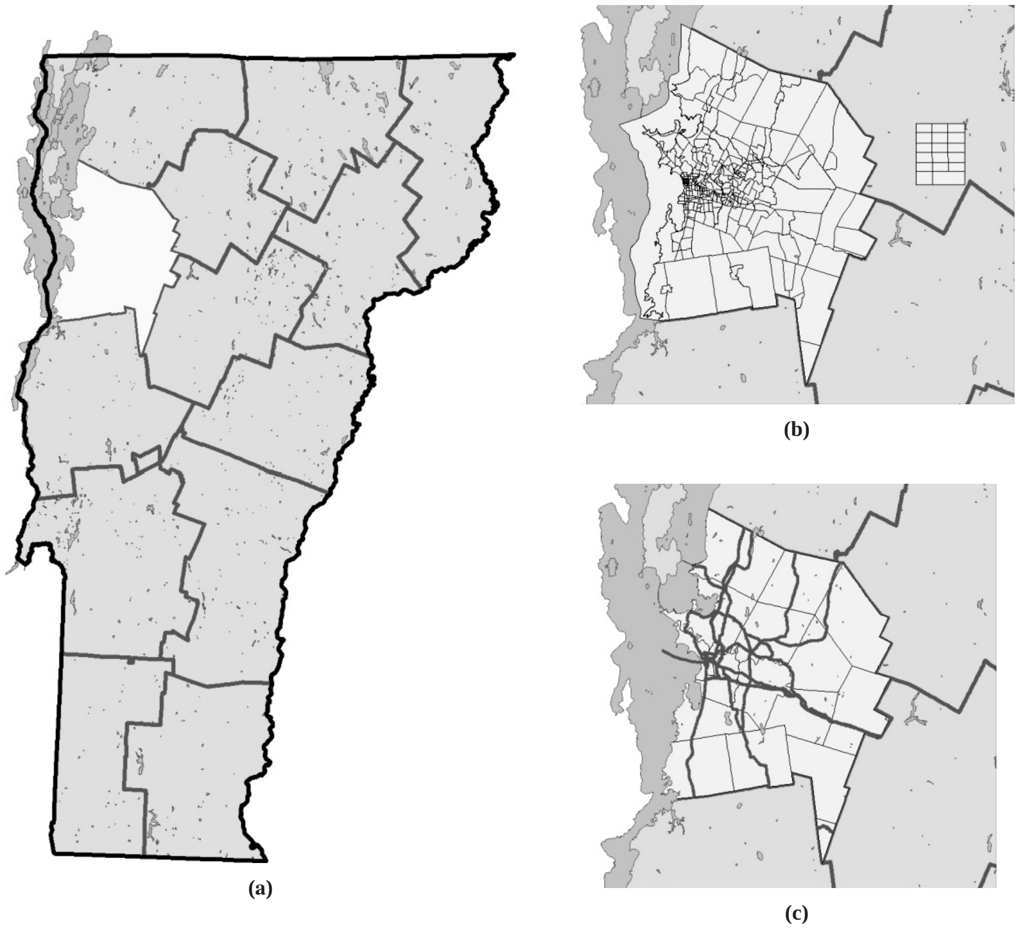


FIGURE 2 Study site: (*a*) Chittenden County, highlighted in white; (*b*) 350 traffic analysis zones; and (*c*) major roads and town boundaries.

these data were converted to digital format by manually entering the records into a database. This process was inherently inefficient and time-consuming, and led to numerous data gaps for which it was not possible to link paper records to digital parcel data. To rectify these gaps in the data, a model of structure age was estimated using an ordinary kriging technique available within ArcGIS Spatial Analyst. Zonal statistics were run for the parcels with null year built values to calculate an estimated year built, and these data will stand as a placeholder for parcels without actual data until town databases have been updated (preferably to a digital format). A similar process was followed to prepare land and improvement value data.

The centerpiece of the UrbanSim model is the grid cells database table. The region of interest is partitioned into a discrete set of cells of user-specified size. For the Chittenden County model, a cell size of 150 m × 150 m was employed, a resolution used in other UrbanSim applications in the past (*13*). At that resolution, there are approximately 64,000 grid cells spanning the entire region. Data are aggregated to the grid cell level and stored in a table that features a set of attributes that define its spatial location and proximity to amenities (e.g., shopping, parks, and the like), proximity to nondesirable features (e.g., waste transfer stations, heavy manufacturing, polluted waterways), presence and areal extent of biophysical features (e.g., percent wetlands, slope, and the like), development and infrastructure characteristics (e.g., land price, housing units, percent roads, sewer boundary), and policy constraints (e.g., zoning). Table 1 provides a partial list of data parameters included in the model, including their respective data sources.

Although much of the data are aggregated to the grid cell level, individual households function as the decision makers (e.g., agents) whose actions have a direct effect on the landscape. UrbanSim v2.8 was used to generate a synthetic population for the region of interest based on socioeconomic characteristics as reported in the U.S. census. Synthesized characteristics include the age of the head of the household, household income, size of household, number of cars, and number of workers. Household synthesis for the 1990 population has been completed, and diagnostic assessments have been performed to ensure the overall characteristics of the actual population have been preserved in the process. UrbanSim does not feature a population model, and instead relies on externally derived control totals for both population and employment. Control totals developed for the Chittenden County Regional Planning Commission (CCRPC) and the CCMPO long-range planning process were used for this model.

After the data collection and processing phase, individual submodels (e.g., land price model; residential, commercial, industrial location choice models; developer location choice model) were estimated using UrbanSim v4.0. The price of land was modeled using multiple linear regression (hedonic analysis), whereas the suite of location choice models were estimated using multinomial logit models. UrbanSim v4.0 includes the necessary statistical tools to estimate the different regression equation types. The set of estimated equations

TABLE 1 Partial List of Data Parameters Used in Chittenden County UrbanSim Model

Data Category	Data Set Name	Data Source
Economic	Land and improvement value Year built for all structures in the county Employment (size, sector, location) Residential units	Grand list from individual town assessor's office Individual town clerk's office Vermont Secretary of State and Claritas[a] CCRPC[b]
Biophysical	Topography, soils, wetlands, water Land cover	Vermont Center for Geographic Information University of Vermont—Spatial Analysis Lab
Infrastructure	Roads Transit	Geographic Data Technology[a] Chittenden County Transit Authority
Planning and zoning	Zoning Conserved land	Information drawn from individual town plans University of Vermont—Spatial Analysis Lab
Demographics	Household characteristics Forecast	U.S. Census: SF1, SF3, 5% public use microdata samples CCRPC[b]/CCMPO[c]

[a]Denotes proprietary data sets.
[b]Chittenden County Regional Planning Commission (CCRPC).
[c]Chittenden Country Metropolitan Planning Organization (CCMPO).

(for each of the submodels) was stored in a database (including model parameters and their corresponding statistical metrics), and model selection was based on Akaike's information criterion, a statistical measure that trades off the complexity of the estimated model against how well the model fits the data.

With the land price model, data are summarized at the grid cell level for a variety of attributes (e.g., commercial square feet, housing units, percent water, distance to Interstate 89, and the like), and the value of a grid cell is regressed against a subset of these characteristics. This set of estimated coefficients is then used to predict the land value of the grid cell for subsequent years. Table 2 displays the covariates used in the land price model, including location effects, policy parameters (e.g., conserved land, within sewer district boundaries), and neighborhood characteristics (e.g., number of households, improvement value). The travel time to the central business district (CBD) covariate (highlighted in bold text in the table) represents the influence of the transport model on the modeled price of land.

The location choice model algorithms are analogous for households and employers. These models predict the probability that a job or household will be located in a specific grid cell using a multinomial logit specification. The models can be generalized for an entire population or stratified by employment sector or household type (e.g., age of head of household, household income, household size). In the current implementation of the Chittenden County model, household location choice is represented with a single model for all household types, whereas nonresidential location choice is based on separate models for commercial and industrial development.

The household location choice generates a set of agents for each time step to represent households moving within the region (based on observed rates of household relocation) as well as new households moving to the area (based on county-level household control totals). The model generates a selection set of alternative locations to consider, and then "chooses" a location from the list of alternatives based on the appropriate multinomial logit equation (e.g., household location choice model, commercial employment location choice model). Selected spaces become unavailable to the remaining households in the queue, and the submodel iterates until all agents are placed or there is no remaining vacant space. Table 3 includes the model parameters for the household location choice model. The home access to population covariate represents the influence of the TDM on household location choices. In general, this parameter indicates that, all else being equal, households prefer to locate away from other households (and the results of the with-TDM run bear this out).

The real estate development model simulates the construction of new development or the intensification of existing development. The model is estimated using observations of prior development patterns through a review of construction permits and year built data. The four years prior to the base year (1986–1989) were examined to ensure an adequate sample of both residential and nonresidential develop-

TABLE 2 Land Price Model Specification with Parameter Estimates

Coefficient Name	Definition	Estimate	*t*-Statistic	Standard Error
Constant		11.16889954	158.3269958	0.070543297
ART	Distance to nearest arterial street	0.424149007	43.89479828	0.00966285
LNIMP	LN grid cell improvement value	0.057201002	41.71829987	0.00137112
ELEV	Elevation	−0.000367311	−30.9116993	1.18826E-05
IND_WIWLK	% industrial w/in walking distance	1.04801E-07	8.793669701	1.19177E-08
INSEWER	Is within sewer district	0.819761992	57.44810104	0.0142696
IS_CONSL	Is conserved land	−0.227327004	−16.22290039	0.0140127
LN_HOUSEHOLDS	LN grid cell # of households	0.162177995	20.76499939	0.00781016
TT_CBD	Travel time to CBD	−0.0187907	−29.9715004	0.000626952
YRBLT	Year built	5.41195E-05	10.17240047	5.32023E-06

TABLE 3 Household Location Choice Model Specification with Parameter Estimates

Coefficient Name	Definition	Estimate	*t*-Statistic	Standard Error
AVE_INC	Average income in the grid cell	1.19E-05	17.2403	6.88E-07
BUILD_AGE	Average age of improvements in the grid cell	−0.001493	−3.8204	0.00039086
COST_INC_RAT	Average cost of improvement to average income ratio	−0.345484	−9.32952	0.0370312
DEV_TYPE_M1	Is zoned mixed use development	0.223611	4.69345	0.0476433
IS_NEAR_ART_300	Is within 300 m of arterial street	2.7211	8.52261	0.31928
IS_NEAR_HIGHWAY	Is within 1500 m of the Interstate	−0.453467	−2.49592	0.181683
LN_COMSF_WWD	LN of commercial square feet w/in walking distance	0.0359928	7.33788	0.00490506
LN_HOME_ACC_POP	LN home access to population by auto	−3.88147	−4.20383	0.923318
LN_HOUSEHOLDS	LN number of households in grid cell	−0.386432	−20.0571	0.0192665
LN_RVAL_PER_RUNIT	LN average value of residential land per residential unit w/in walking distance	−0.348223	−11.6168	0.0299759
%_LOW_INC_WWD_IF_HIGH_INC	% low income households w/in walking distance if high income household	−0.0451663	−19.3233	0.0023374
%_LOW_INC_WWD_IF_LOW_INC	% low income households w/in walking distance if low income household	0.0543723	19.3845	0.00280494
VAC_RES_UNITS	# of vacant residential units	−0.682592	−63.5107	0.0107477

ment events. Supply shortages trigger additional development in subsequent years, whereas surpluses cause the pace of development to slow. All new development is subject to zoning constraints based on user-specified decision rules (e.g., density, required streamside buffer, and the like).

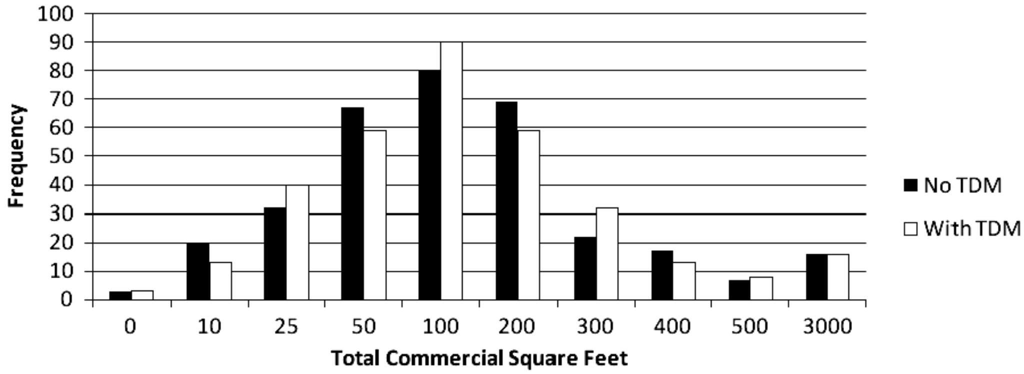
To simulate land use interactions with the transportation network, the CCMPO's TDM was linked to UrbanSim. The travel model was developed using TransCAD v4.9 (Caliper Corporation), a transportation planning software package, based on a geographic information system, that follows the typical four-step process for travel demand modeling, including trip generation, trip distribution, mode split, and traffic assignment. The travel model is based on household travel diaries collected for CCMPO. Traffic assignment is based on an equilibrium model that employs an iterative procedure to reach convergence. The model was calibrated against observed a.m. and p.m. peak conditions (*14*). A Python script was written to pass data between UrbanSim and TransCAD in three steps: (*a*) export land use, number of households, and number of jobs for each trip generator type (low, medium low, medium high, high, school, and hotel or motel) from UrbanSim to TransCAD; (*b*) run the travel model; and (*c*) export travel model results (e.g., accessibilities) from TransCAD to the UrbanSim data cache. Once the land use data are exported, TransCAD is invoked and passed the traffic analysis zone (TAZ)-scale aggregates of households and jobs, by generator type, for the current simulation year of the land use model. TransCAD then generates a TAZ-scale origin–destination matrix of logsum accessibilities for each travel mode simulated (transit, auto, walk or bike) as well as a composite measure of all modes. These data are written into the UrbanSim data cache for the current simulation year, and the measures of accessibility are used in subsequent model steps for location choice decisions.

For the purposes of this research, the integrated model was run using UrbanSim v4.0 for the period 1990 to 2030. The land use model ran on an annual time step, whereas the travel model was run on 5-year intervals (beginning in 1990). In the case where the travel model was not linked to the simulation, accessibilities were estimated for the base year using the travel model, and these accessibilities were assumed constant for the duration of the model run.

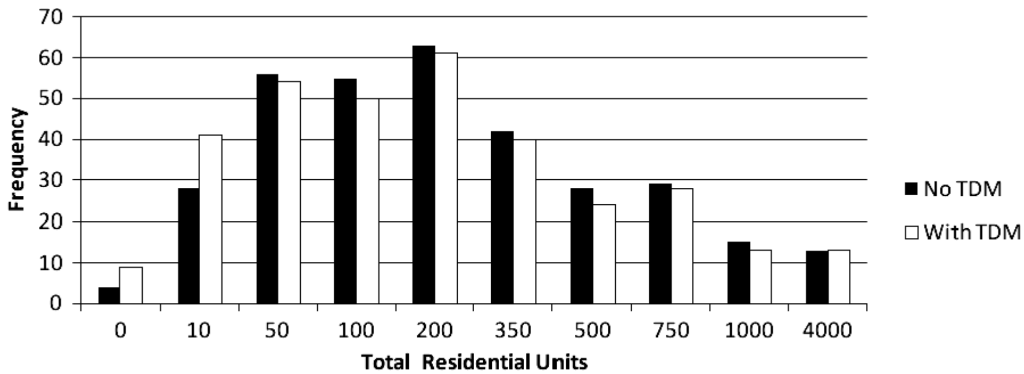
RESULTS

To compare the results of the model runs with and without the endogenous TDM, a number of outputs are presented. All of the modeled outputs are aggregated to the TAZ scale. First, histograms were plotted comparing total commercial square feet for each model for the year 2030 and total residential units for each model for 2030 (Figure 3). In terms of total commercial square feet, the extreme low (0 commercial square feet) and the high end (greater than 500,000 commercial square feet), are relatively consistent between the two models. There were three TAZs with 0 commercial square feet in the base year data set, and both model runs conclude with 0 commercial square feet in the same three TAZs. Consistency on the high end is not surprising because of the limited number of large-scale projects that occur within the county. The middle of the distribution, however, is quite muddled. One possible explanation for this is the lack of large-scale commercial development in the county. Big-box commercial centers are generally located in a select few places within the county and land use restrictions prohibit their placement in many others. As a result there is a tendency to develop more small locations as opposed to a few large ones. For the cases in which the frequency of observation was greater for the without-TDM run, the additional TAZs were almost exclusively located in close proximity to Burlington (the regional CBD). This suggests that the lack of congestion in the without-TDM model did not discourage development within these TAZs as it is likely to have done for the with-TDM case. Of note in the residential units histogram is the disparity in frequency at the low end of the scale and the relative equality at the upper end of the scale. The simulation with the TDM appears to distribute residential development over a greater number of TAZs.

Histograms were also plotted to show the change in commercial square feet and residential units over time (Figure 4 and Figure 5, respectively). Three time periods are included: 1990, 2010, and 2030. The center plot of both Figures 4 and 5 represents the difference between the two model runs (without – with TDM) for 2010 and 2030, and visually suggests that there are significant differences in both the number of residential units and amount of commercial square footage per TAZ when broken down by bins. When the commercial



(a)



(b)

FIGURE 3 Comparison of modeled results for the year 2030 for simulations run with and without TDM: (*a*) difference in total commercial square feet at the TAZ scale and (*b*) difference in modeled outputs for the total number of residential units.

data results are compared, it appears that congestion effects (in the with-TDM model) deter development beyond 300,000 ft^2. The residential data show that the with-TDM model had many more TAZs with no or low levels of residential units (<10) than the without-TDM model, and fewer TAZs with high numbers of residential units, suggesting a less dense residential configuration.

Variance ratio tests were performed to determine whether the standard deviations for residential units per TAZ in 2030 were equal for the two model configurations. The same test was performed for commercial square footage. Significant differences were found between the with- and without-TDM implementations in the variance of predicted total residential units but not for total commercial square feet. Results are provided in Table 4 and Table 5. These same tests were performed for the year 2010 (detailed results are not presented here) and neither test resulted in significant differences. Linear regressions were also run (detailed results are not presented here) between commercial square footage in 2030 under the with-TDM model versus the same variable from the without-TDM model. Consistent with the variance tests, the R-squared for the commercial square foot variables was very high, at 0.98, while the R-squared for total residential units was lower, at 0.83.

To examine the spatial patterns of land use change over the 40-year simulation period tabular data were joined to a geographic data set that defines the TAZ boundaries to create choropleth difference maps of the modeled outcomes (Figure 6). The difference between the two model runs was displayed as a percentage of the with-TDM run. These maps show that differences tend to be small in the more central areas around Burlington (near the black dot on the map) and adjacent to Interstate 89 (not shown), whereas there is heterogeneity in the more peripheral areas. This is particularly the case for the difference in predicted values for residential units. Negative values (white to light gray) indicate that more development occurred when the TDM was run, whereas positive values (black) denote more development occurring when the travel model is not run. Unlike the predicted values for number of residential units in a TAZ, there does not appear to be a discernable pattern in the difference between the predicted commercial square feet.

DISCUSSION OF RESULTS

These results indicate that running a land use model with an endogenous TDM yields different results from running the model based on a static set of regional accessibilities. Further, the results from the with-TDM versus without-TDM model suggest that there are different distributions of development counts at the TAZ level for residential development. The maps in Figure 6 suggest that although centrally located TAZs tend to see relatively little differences, the big differences occur in the more distant or peripheral TAZs. Why then do some of these more peripheral TAZs see a positive differential while others see a negative one? The answer probably has to do with the different processes that are modeled by the TDM: accessibility to activities and congestion. The pattern displayed suggests some peripheral TAZs (such as those in the east of the county) have higher modeled

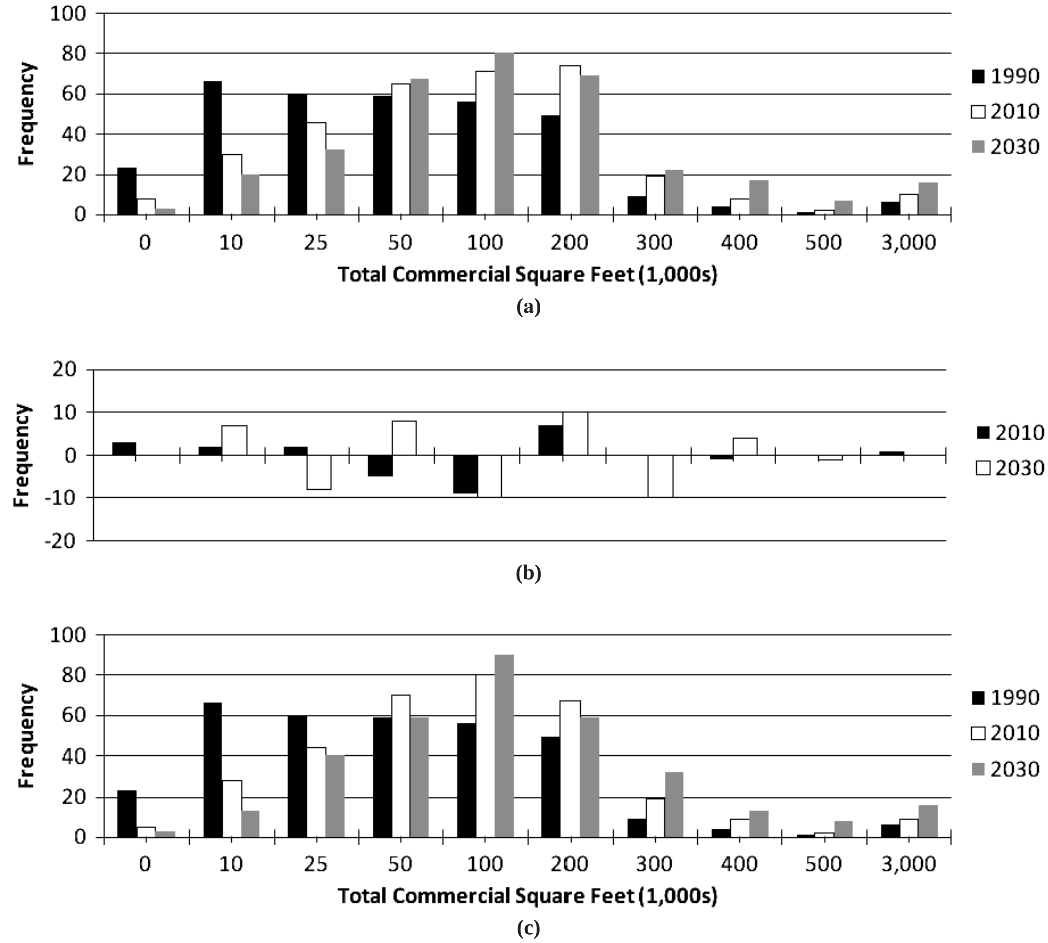


FIGURE 4 Distribution of commercial square feet by TAZ showing differences over time for simulations (*a*) without TDM and (*c*) with TDM; (*b*) histogram shows the difference (without TDM minus with TDM) between two model runs.

development with a TDM because the TDM accounts for the increased proximity of destinations (and the resulting increase in overall accessibility), thereby making these locations more amenable to new development. Meanwhile, some peripheral TAZs (such as those in the north of the county) have lower modeled development with a TDM because they already have good accessibility (the red TAZs in the north are located on either side of an Interstate) and were viable development locations based on the initial accessibility values in the without-TDM simulation. Additionally, because the without-TDM simulation has no way to account for increased congestion, these locations continue to look good for development throughout the entire simulation, and therefore accumulate significant excess development when compared to the with-TDM simulation. The model behavior in the without-TDM simulation defies conventional logic that congestion effectively decreases accessibility, thereby reducing development.

CONCLUSIONS

An integrated land use and transportation modeling system was implemented for Chittenden County to test the model outputs for differences based on simulations run with and without a dynamically linked TDM. Statistical tests indicate that the simulations yield different distributions of residential development over the 40-year simulation period. This result was not the case for total commercial square feet, however. A visual inspection of the spatial distributions of development suggests a more compact pattern of development is produced when running the model without the TDM. One logical next step will be to prepare a complete set of 2000-era data to perform model validation, and improve the understanding of whether modeling land use change in a relatively small metro area benefits from the inclusion of an aggregate-scale TDM. It might prove also interesting to include additional transportation related covariates within the different submodels to see if results are affected for a similar set of hypothesis tests from an alternative model configuration.

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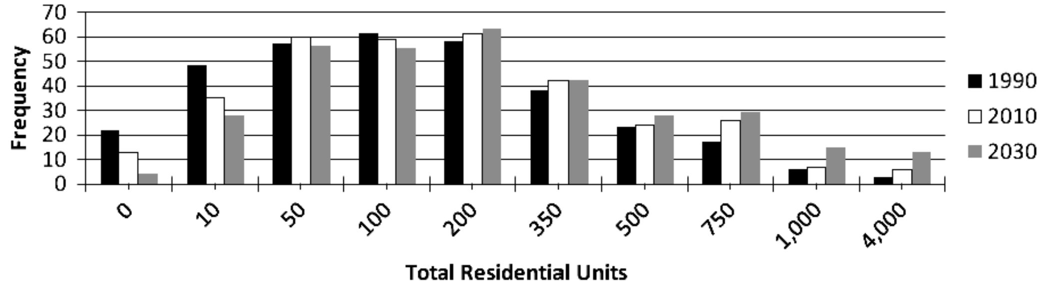

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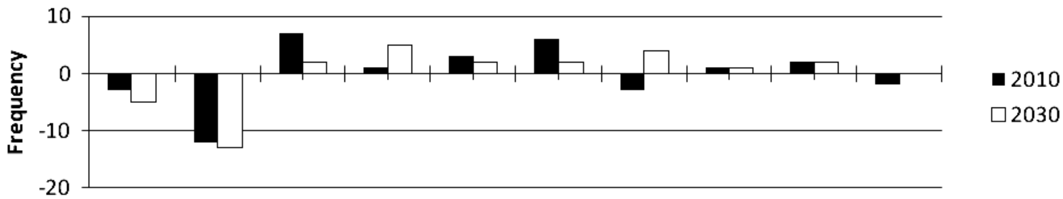

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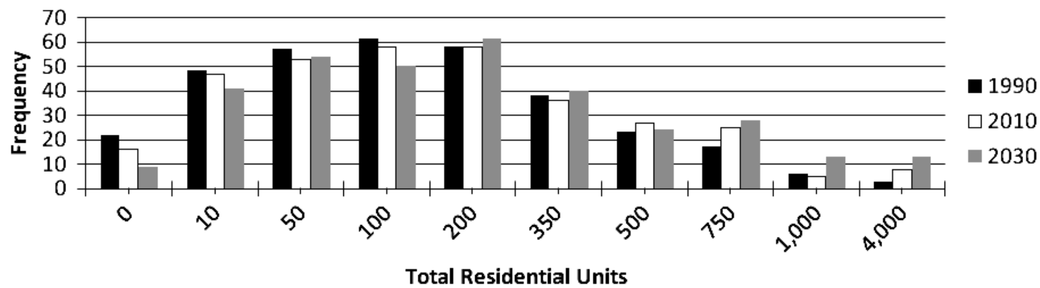

(c)

FIGURE 5 Residential units aggregated to the TAZ level showing differences over time for simulations (*a*) without TDM and (*c*) with TDM; (*b*) histogram shows the difference (without TDM minus with TDM) between two model runs.

TABLE 4 Variance Ratio Test Comparing Total Residential Units at TAZ Scale

Variable	Observations	Mean	Std. Err.	SD	95% Conf.	Interval
No TDM	333	258.5706	18.05551	329.4821	223.0529	294.0882
With TDM	333	258.5706	22.53505	411.2261	214.2411	302.9001
Combined	666	258.5706	14.4272	372.3223	230.2422	286.8989

NOTE: Ratio = sd(res1029)/sd(res1034); $f = 0.6420$; H_o; ratio = 1; degrees of freedom = 332, 332; H_a: ratio < 1; H_a: ratio != 1; H_a: ratio > 1; Pr($F < f$) = 0.0000; 2*Pr($F < f$) = 0.0001; Pr($F > f$) = 1.0000.

TABLE 5 Variance Ratio Test Comparing Total Commercial Square Footage at TAZ Scale

Variable	Observations	Mean	Std. Err.	SD	95% Confidence Interval
No TDM	333	155,097.7	15,324.13	279,639.2	124,953.1 to 185,242.3
With TDM	333	155,256.1	14,988.89	273,521.6	125,770.9 to 184,741.3
Combined	666	155,176.9	10,709.87	276,389.3	134,147.7 to 176,206.1

NOTE: Ratio = sd(comm1029)/sd(comm1034); $f = 1.0452$; H_o: ratio = 1; degrees of freedom = 332, 332; H_a: ratio < 1; H_a: ratio != 1; H_a: ratio > 1; Pr($F < f$) = 0.6564; 2*Pr($F > f$) = 0.6872; Pr($F > f$) = 0.3436.

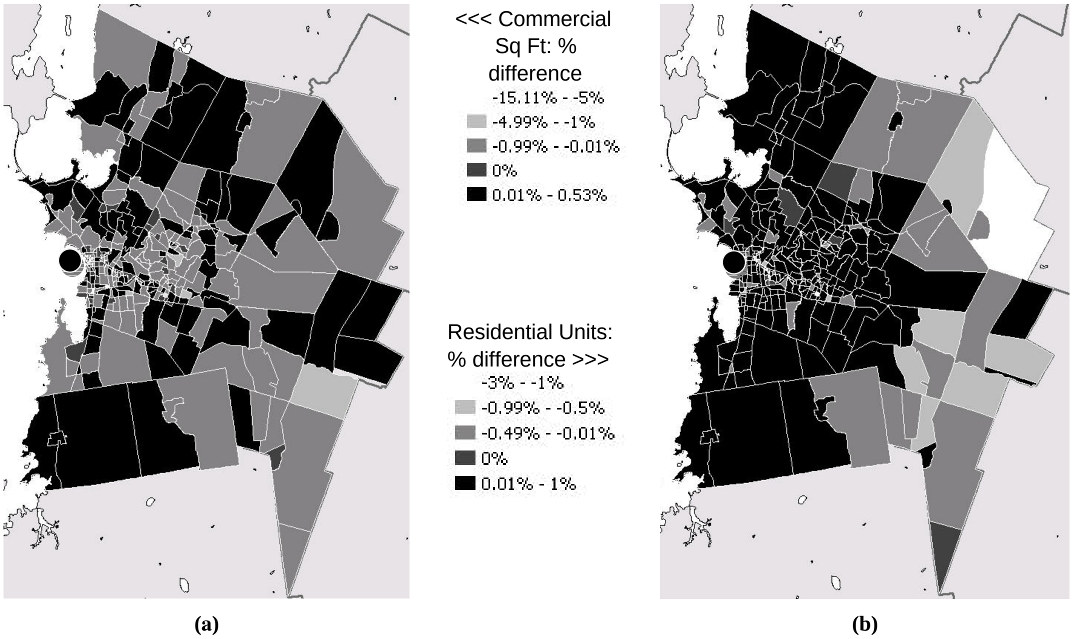

FIGURE 6 Percent difference in (*a*) predicted commercial square feet and (*b*) predicted residential units at the TAZ geography.

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