Title: Testing an integrated land use and transportation modeling framework for a small metropolitan area

Corresponding Author
Brian Voigt
Spatial Analysis Lab - Rubenstein School of Environment and Natural Resources
University of Vermont
81 Carrigan Drive
Burlington, VT 05405
tel 802.656.3324
fax 802.656.8683
brian.voigt@uvm.edu

Co-authors
Austin Troy, PhD
Spatial Analysis Lab - Rubenstein School of Environment and Natural Resources
University of Vermont
81 Carrigan Drive
Burlington, VT 05405
tel 802.656.3324
fax 802.656.8683
Austin.troy@uvm.edu

Brian Miles
Spatial Analysis Lab - Rubenstein School of Environment and Natural Resources
University of Vermont
81 Carrigan Drive
Burlington, VT 05405
tel 802.656.3324
fax 802.656.8683
brian.miles@uvm.edu

Alexandra Reiss
Spatial Analysis Lab - Rubenstein School of Environment and Natural Resources
University of Vermont
81 Carrigan Drive
Burlington, VT 05405
tel 802.656.3324
fax 802.656.8683
areiss@uvm.edu

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ABSTRACT

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 versus an assumption of static regional accessibilities over time. Using the UrbanSim land use model, two versions of a 40 year simulation for the County, one with a travel demand model (TDM) and the other without were compared. In the first version, UrbanSim was integrated with the TransCAD four-step travel demand model, allowing regional accessibilities to be recalculated at regularly scheduled intervals. In the second version, TransCAD was used to compute year 2000 accessibilities, and these values were held constant for the duration of the model run. The results indicated some significant differences in the modeled outputs. In particular, while centrally located traffic analysis zones (TAZs) reveal relatively little difference between the two models, the differential within peripheral TAZs is both more pronounced and heterogeneous. The pattern displayed suggests 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.

INTRODUCTION

While 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, 3, 4, 5, 6) as well as by the Federal Highway Administration (7). In fact, under the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 and to a lesser extent the Transportation Equity Act for the Twenty First Century (TEA-21) 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. 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 an 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 (2004) 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 suggest 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, 10, 11) is a land use model currently under development at the University of Washington’s Department of Urban Design and Planning. A review of land use models found UrbanSim to be one of the best land use models because of its ability to be integrated with a number of different proprietary and open-source transportation models, among other reasons

(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 comprised of a suite of sub-models 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 endogenize factors 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.

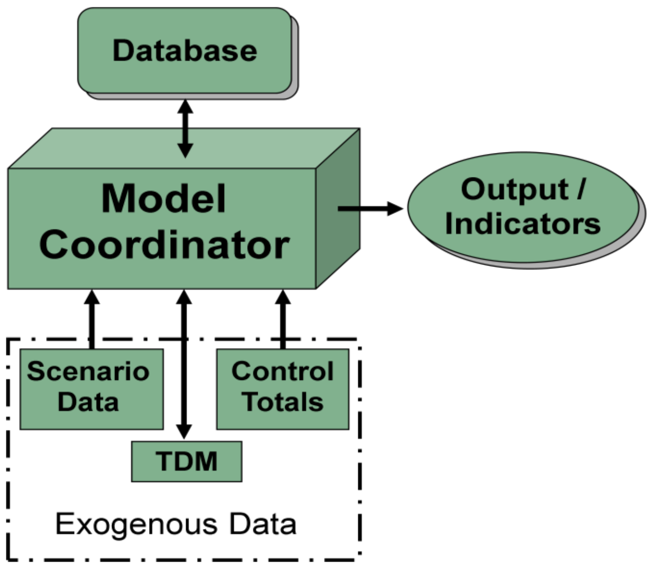

FIGURE 1 UrbanSim model architecture.

The model is based on a dynamic disequilibrium approach that represents systemic changes occurring at different temporal scales, and combines elements of both the cellular automata and agent-based approaches to modeling land use change. Physical characteristics of the landscape are aggregated at the cellular level, while individual actors make decisions regarding employment and household location. The individual modeling components communicate through a common data storage tool (a MySQL database), where the outputs from one sub-model can serve as the inputs for one or more of the others. Exogenous inputs to the model include macroeconomic indicators of employment conditions and real estate transactions, outputs from an independent travel demand model 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. Since 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. For the purposes of the Chittenden County implementation, the travel demand model is run every five years, or when significant changes have been made to the transportation network (e.g. addition of new highway interchange or the construction of a new road). The land use change model components are run on an annual time step simulating partial equilibration as actors adjust to the rate of change of fluxes within the economic system or the housing market. The annual time step simulates the evolution of the household and employment locations at the individual level and the evolution of the real estate market at the grid cell level. Where required data does not exist for a municipality, the model architecture allows the user to disable model components. Additionally, since 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. The broad range of data inputs yield a number of modeled outputs that generally fit within the following categories: transportation, environmental impact, land use and real estate development, employment, and households and population (UrbanSim.org 2007). These outputs are calculated from the data cache generated by the model run and are assembled into database tables. Model outputs can then be imported into a geographic information system (GIS) or statistical software package for graphical display and further analysis.

UrbanSim has a number of standard indicators based on Value Sensitive Design theory, which considers human values in the design of the model outputs (13). Key components of this theory allow for the creation of indicators that are important to both direct and indirect stakeholders defined as those operating the model (planners and modelers) and those affected by the model (citizens), respectively (14). The inclusion of indirect stakeholder values is a unique characteristic of UrbanSim; it represents a specific intent to facilitate stakeholder interaction for a diverse group of interests and provide the ability to run scenarios to assess effects on a broad range of user values (14).

RESEARCH OBJECTIVES

The primary objective of this investigation is to test the effects of including vs. excluding an endogenized travel demand model 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? As population and employment grow, the amount of total travel should also grow. However, what it 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 either lower congestion better overall accessibility or both. If the results of the two models displayed relatively little difference, this would suggest that the added complexity of dynamically integrating the travel model does not cause the system to reach any critical congestion thresholds which would in turn affect development patterns. In such a case, it would suggest that for a system with characteristics like Chittenden County, endogenizing regional accessibilities may not be necessary to predict land use.

STUDY SITE

Chittenden County, VT (Figure 2) was selected as the case study site for this research for several reasons. First, as a metropolitan area of relatively low population (146,671 according to the US 2000 census), the geography of the County (covering a total area of 540 square miles) is extremely tractable from a modeling standpoint. Second, the County is relatively isolated (3 hours from the nearest major American city) which means that it can be modeled as a closed system, an assumed but frequently violated assumption of land use modeling. Thirdly, the

County is an excellent place to study patterns of urbanization because it remains relatively undeveloped in the several towns outside the Burlington metro area (Vermont's largest city) and as a result has diverse possible future trajectories.

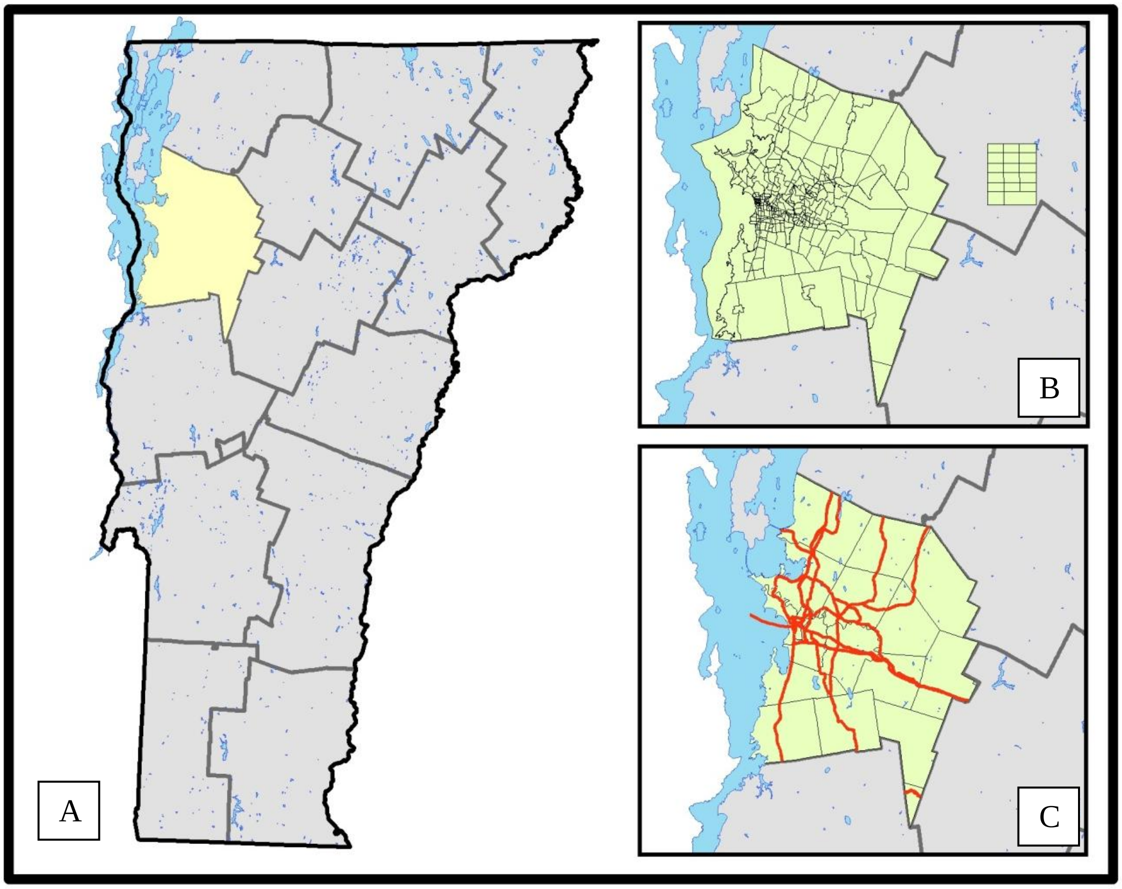

FIGURE 2 A) The study area Chittenden County, VT, B) The 350 traffic analysis zones in Chittenden County, and C) Major roads and town boundaries in Chittenden County, VT.

In addition, several research partners have been modeling this region for many years providing us with a rich set of data and model tools, including a calibrated TransCAD model and an UrbanSim implementation, a PARAMICS model of the County and two implemented synthetic population generation models that will facilitate the TRANSIMS implementation. Finally, members of our research team have recently been awarded one out of only two national U.S. DOT grants to implement the TRANSIMS model for Chittenden County. With this array of models, Chittenden County can serve as a national showcase for the development, evaluation, testing, calibration and benchmarking of integrated land use and transportation models for sustainable transportation policy development.

DATA DEVELOPMENT

Spatial data processing and analysis was performed using ESRI's ArcGIS 9.2 platform, while tabular data is handled using Microsoft Access. The compiled base year data set is 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 both improve the work flow and ensure consistency in data handling. UrbanSim requires a broad range of datasets (see Table 1) to operationalize the model. Additionally, the model can be customized to include optional data sets that define unique characteristics of the area of study. The data development stage for the Chittenden County model was complicated by two primary factors: 1) most of the data sets for the model come from the individual towns within the County, which made it necessary to standardize the data in a consistent format so that they could be used together, and 2) a majority of the data sets were not stored in a digital format, which made it necessary to translate paper records to digital databases, and geocode the data to generate spatial data that could be input into the model.

TABLE 1 Abbreviated list of UrbanSim Data Parameters Used in the Chittenden County Model

Data Category	Data Set Name	Data Source
Economic	Land and improvement value	Grand List from town assessor's office
	Employment (size, sector, location)	VT Secretary of State and Claritas*
	Residential Units	CCRPC
Biophysical	Topography, soils, wetlands, water	Vermont Center for Geographic Information
	Land Cover	University of Vermont – Spatial Analysis Lab
Infrastructure	Roads	GDT*
	Transit	Chittenden County Transit Authority
Planning & Zoning	Zoning	Information drawn from individual town plans
	Conserved land	University of Vermont – Spatial Analysis Lab
Demographics	Household characteristics	US Census: SF1, SF3, 5% PUMS
	Forecast	CCRPC / CCMPO

* denotes proprietary data sets

The centerpiece of the UrbanSim model is the *gridcells* database table. The region of interest is partitioned into a discrete set of cells of user-specified size. For the Chittenden County implementation, a cell size of 150 square meters was selected, a resolution used in other UrbanSim implementations in the past (15). At that resolution, there are approximately 64,000 grid cells. Data is aggregated to the grid cell level and stored in the *gridcells* table (which features more than 30 attributes that define not only its spatial location (e.g. contained within a specific block group or TAZ, distance to highway or airport), but also the presence and description of natural features (e.g. percent wetlands, slope, etc.) as well as development and infrastructure characteristics (e.g. number of housing units, percent roads).

In cases where data does 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 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 where 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 this data will stand as a place holder 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.

While much of the data is 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 version 2.8 includes a tool to generate a synthetic population for the region of interest based on socio-economic characteristics as reported in the US Census. Synthesized characteristics include the age of the head of the household, household income, size of household, number of cars, and the number of workers. Household synthesis for the 1990 population has been completed, and a number of diagnostic assessments have been performed to ensure the overall characteristics of the 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. This application will use control totals developed for the Chittenden County Regional Planning Commission (RPC) and the Chittenden County Metropolitan Planning Organization.

Following the data collection and processing phase, UrbanSim's individual sub-models (e.g. land price model, residential / commercial / industrial location choice models, developer location choice model, etc.) are estimated using two types of regression techniques. The land price model is estimated using multiple linear regression (hedonic analysis), while the suite of location choice models are estimated using multinomial logit models. UrbanSim includes the necessary statistical tools to estimate the different equation types. The entire set of estimated equations was stored in a database (including individual model parameters and corresponding statistical metrics), and model selection was based on Akaike's Information Criterion (AIC), a statistical measure which trades off the complexity of the estimated model against how well the model fits the data.

When estimating the land price model, data is summarized at the grid cell level for a variety of attributes (e.g., commercial square feet, housing units, percent water, distance to Interstate 89, etc.), and the value of a grid cell is regressed against 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 range of covariates currently used in the land price model, including spatial parameters (e.g. distance to arterial), policy parameters (e.g. is conserved land, within sewer district boundaries), and neighborhood characteristics (e.g. number of households, improvement value).

The location choice models (for households and employers) predict the probability that a new 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). The set of locations is a combination of the vacant locations and grid cells available to accommodate additional development (of the specified type). Models are analogous for employment and household location choices. A set of agents is generated in each time step to represent households moving within the region (based on observed rates of household relocation) as well as new households that are moving in to the area (based on County-level household control totals). Each job or household in the unplaced queue is processed in random order. 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). The selected space becomes unavailable to the remaining jobs or households in the queues, and the sub-model continues to run until all agents are placed or there is no remaining vacant space. Table 3 includes the model parameters for the Commercial Employment Location Choice Model.

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 gridcell 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
TTT_CBD	Travel time to CBD	-0.0187907	-29.9715004	0.000626952
YRBLT	Year built	5.41195E-05	10.17240047	5.32023E-06

TABLE 3 Commercial Employment Location Choice Model Specification with Parameter Estimates

Coefficient Name	Definition	Estimate	t_statistic	Standard Error
D2LAKE	Distance to Lake Champlain	0.00351737	7.067900181	0.000497655
DEV_TYPE_C3	Is grid cell zoned med density commercial	-0.332347006	-9.465279579	0.035112198
JOBS_WWD	Jobs w/in walking distance	0.00591651	6.749310017	0.00087661
LN_IMP_VALUE	LN grid cell improvement value	-0.045417301	-4.670100212	0.00972513
PER_RES_LAND	% residential land	-0.00150707	-3.38609004	0.000445077
RES_DENSITY	Residential density	-0.044820201	-10.33619976	0.00433623

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 either through a review of construction permits or year built data. Supply shortages for housing or employment locations trigger additional development in subsequent years, while surpluses cause the pace of development to slow. All new development is subject to constraints based on user-specified decision rules (e.g., density, required streamside buffer, etc.). Finally, other user-specified exogenous inputs guide the scenario modeling process. While the model framework allows for an extensive set of possible scenarios, the critical component of this process is converting proposed changes to the system into a data format the model can both utilize and understand. A wide range of scenarios, including changes to control totals or infrastructure (e.g. new Interstate interchange), are relatively straightforward from both theoretical and technical standpoints. Alternative land use policies, however, can prove more difficult to simulate, requiring changes to several of the data base tables (e.g. *gridcells, development event constraints, etc.)*.

To simulate interactions with the transportation network, a pre-existing implementation of a travel demand model developed for the Chittenden County Metropolitan Planning Organization by RSG, Inc. was used. This implementation uses TransCAD v4.9 (Caliper Corp.), a GIS-based transportation planning software package that follows the typical four-step travel demand modeling process, including trip generation, trip distribution, mode split and traffic. A python script was developed which passes data between UrbanSim and TransCAD in a three step process. These steps include: 1) exporting land use, number of households, and number of jobs for each trip generator type (low, medium low, medium high, high, school, and hotel/motel) from UrbanSim to TransCAD; 2) running the travel model; 3) exporting 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 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 (OD) matrix of logsum accessibilities for each travel mode simulated (transit, auto, walk/bike) as well as a composite 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 model was run between 1990 and 2030 using an annual time step for the land use model and 5-year intervals for the travel model (beginning in 1990). For the case where the travel model was not dynamically linked to the simulation, regional accessibilities were estimated using the travel model, and these accessibilities were assumed to remain constant for the duration of the model run.

RESULTS

To compare the results of the model runs with and without the endogenous travel demand model, a number of outputs are presented. All of the modeled outputs are aggregated to the TAZ scale. First, we plotted histograms 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 end, 0 commercial square feet, and the high end, greater than 500,000 commercial square feet, appears to be relatively equal. The middle of the distribution is quite muddled. 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.

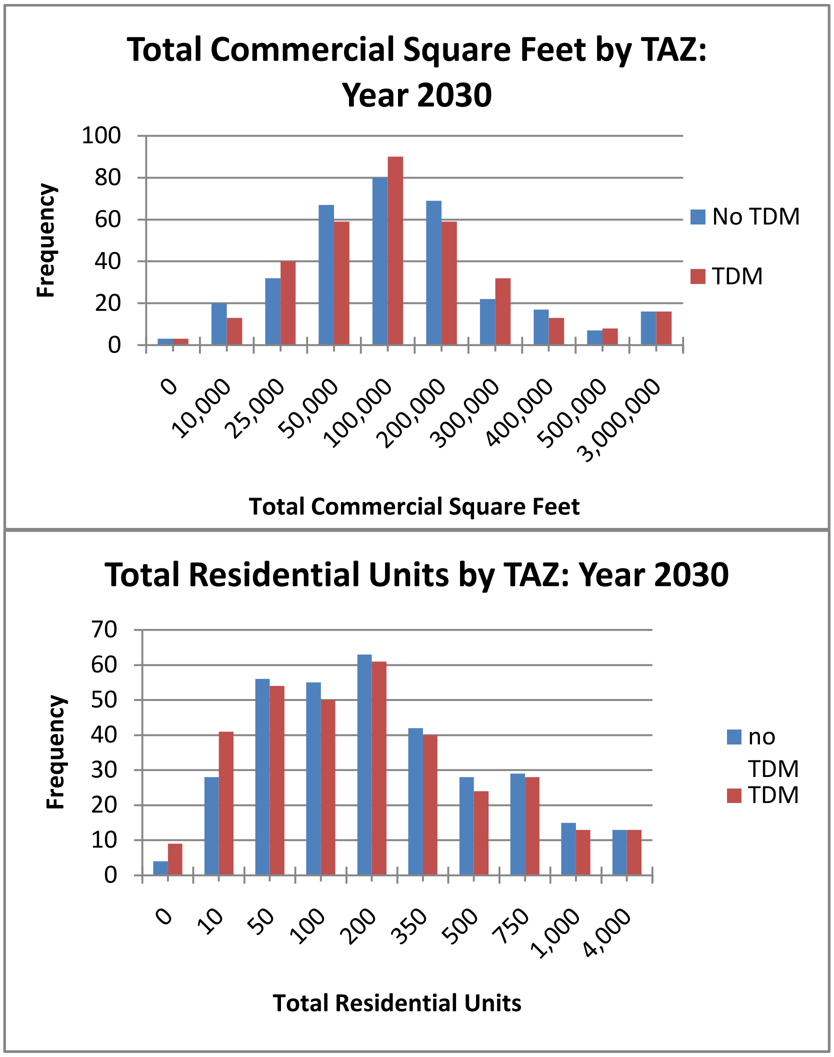

FIGURE 3 A comparison of modeled results for the year 2030 for simulations run with and without the travel demand model. The top histogram displays differences in total commercial square feet at the TAZ scale, while the bottom histogram shows the difference in modeled outputs for the total number of residential units.

Histograms were also plotted to show the change in those two variables over time (Figure 4 and Figure 5). Three time periods are included: 1990, 2010 and 2030. Figure 4 visually suggests that there are significant differences in both the number of residential units and amount of commercial square footage when broken down by bins. In particular, it shows that the with-TDM model had many more TAZs with no or low levels of residential units (<10) than the without-TDM model. Variance ratio tests were performed in Stata to test the equality of standard deviations for residential units for the year 2030 between 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. Linear regressions were also run (detailed results 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 the residential units variables was lower, at 0.83.

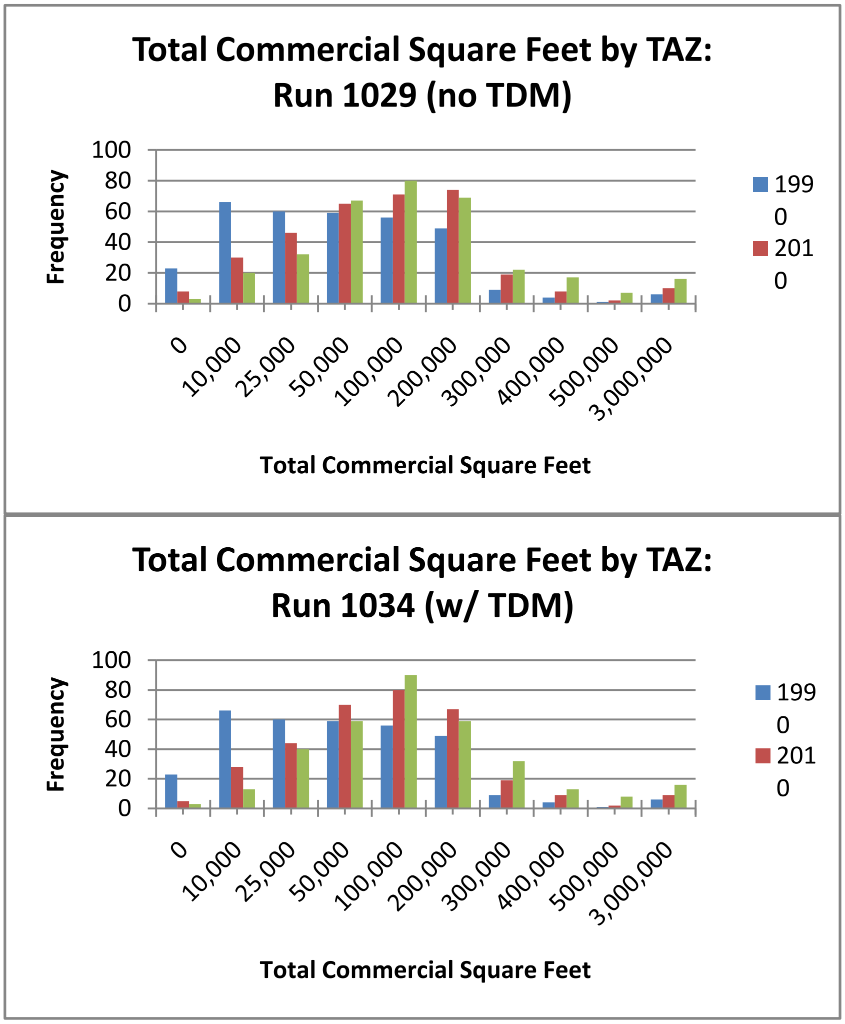

FIGURE 4 Histograms of the distribution of commericial square feet by TAZ showing differences over time for simulations with (above) and without (below) an integrated travel demand model.

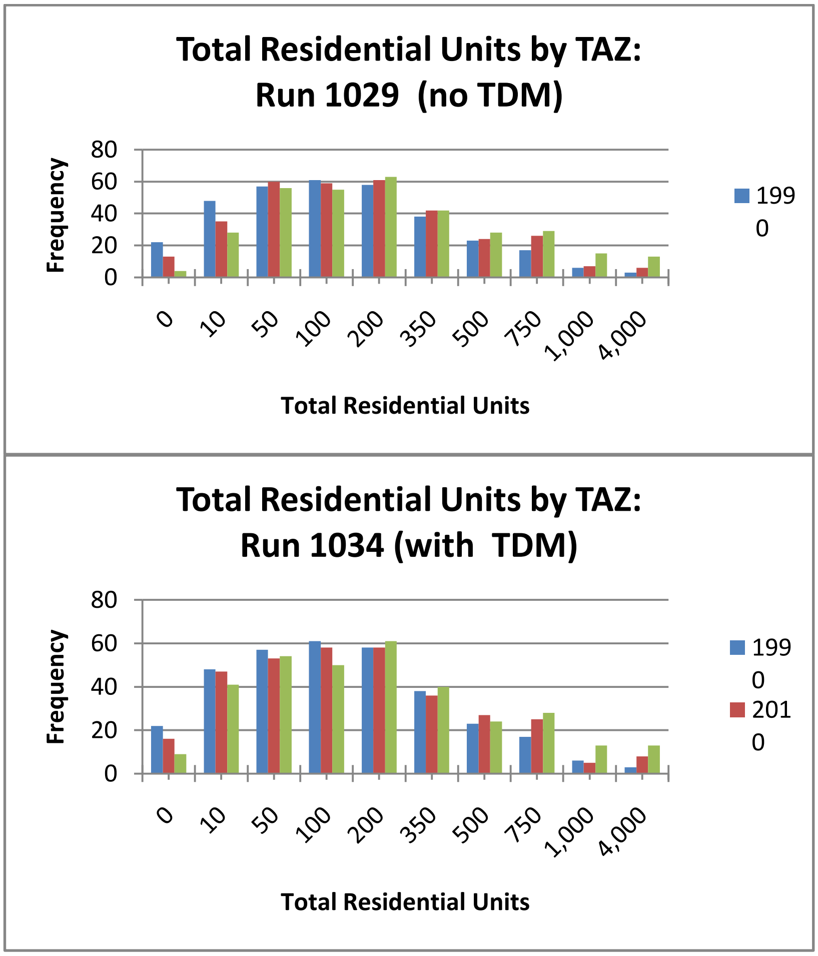

FIGURE 5 Histograms of residential units aggregated to the TAZ level showing differences over time for simulations with (above) and without (below) an integrated travel demand model.

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

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
res1029	333	258.5706	18.05551	329.4821	223.0529	294.0882
res1034	333	258.5706	22.53505	411.2261	214.2411	302.9001
combined	666	258.5706	14.4272	372.3223	230.2422	286.8989
ratio = sd(res1029) / sd(res1034)				f = 0.6420		
Ho: ratio = 1			degrees of freedom = 332, 332			
Ha: ratio < 1			Ha: ratio != 1	Ha: 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 the TAZ Scale

Variable |	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
comm1029	333	155097.7	15324.13	279639.2	124953.1	185242.3
comm1034	333	155256.1	14988.89	273521.6	125770.9	184741.3
combined	666	155176.9	10709.87	276389.3	134147.7	176206.1
ratio = sd(comm1029) / sd(comm1034)				f = 1.0452		
Ho: ratio = 1			degrees of freedom = 332, 332			
Ha: ratio < 1		Ha: ratio != 1		Ha: ratio > 1		
Pr(F < f) = 0.6564		2*Pr(F > f) = 0.6872		Pr(F > f) = 0.3436		

In order to examine the spatial patterns of land use change over the forty year simulation period tabular data was joined to a geographic dataset that defines the TAZ boundaries. The with-TDM modeled values for the year 2030 were subtracted from the without-TDM modeled values for both the commercial square feet and the residential units. Using ArcGIS two maps which illustrate the spatial distribution of differences in commercial square footage and residential units were generated using ArcGIS v9.2. 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, while there is heterogeneity in the more peripheral areas. This is particularly the case for the predicted values of total residential units.

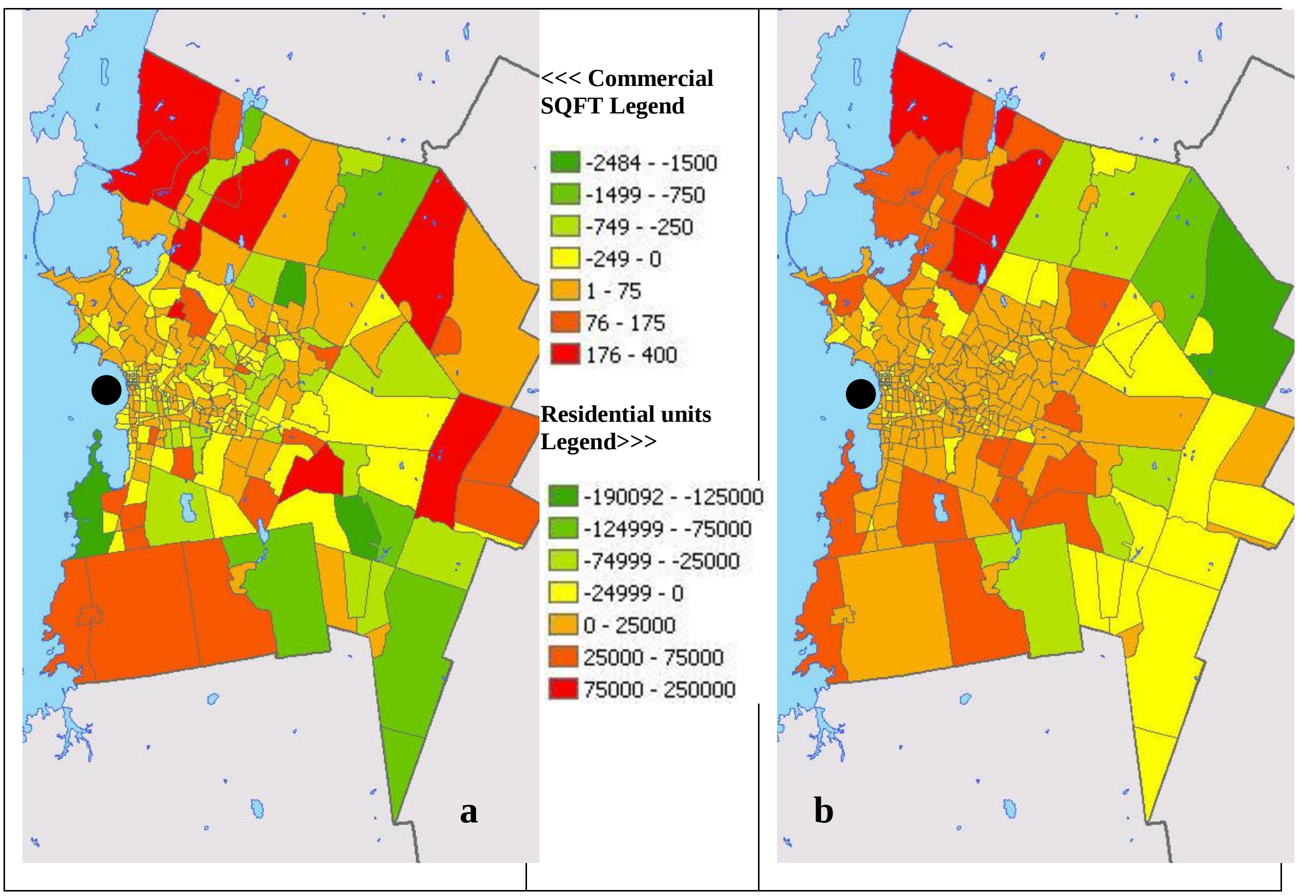

FIGURE 6 Differences in predicted commercial square feet (A) and residential units (B) at the TAZ geography. Negative values indicate that more development occurred when the travel demand model was run, while positive values denote more development occurring

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 development of commercial square feet.

DISCUSSION

These results indicate that running a land use model with an endogenous travel demand model yields different results from running the model based on a static set of regional accessibilities. Further, the results from the with-TDM vs. no-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 while 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 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, since 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 the logic that since congestion effectively decreases accessibility, it also should reduce development.

CONCLUSIONS

An integrated land use and transportation modeling system was implemented for Chittenden County, VT to test the model outputs for differences based on simulations run with and without a dynamically linked travel demand model. Statistical tests indicate that the simulations yield different distributions of residential development over the forty year simulation period. This was, however, not the case for total commercial square feet. A visual inspection of the spatial distributions of development suggests a more compact pattern of development is produced when running the model without the travel demand model. A logical next step will be to prepare a complete set of 2000-era data to perform model validation, and improve our understanding of whether modeling land use change in a relatively small metro area benefits from the inclusion of an aggregate-scale travel demand model.

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