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Integrating a traffic router and microsimulator into a land use and travel demand model

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This paper describes one of the first known attempts at integrating a dynamic and disaggregated land-use model with a traffic microsimulator and compares its predictions of land use to those from an integration of the same land-use model with a more traditional four-step travel demand model. For our study area of Chittenden County, Vermont, we used a 40-year simulation beginning in 1990. Predicted differences in residential units between models for 2030 broken down by town correlated significantly with predicted differences in accessibility. The two towns with the greatest predicted differences in land use and accessibility are also the towns that currently have the most severe traffic bottlenecks and poorest route redundancy. Our results suggest that this particular integration of a micro-simulator with a disaggregated land-use model is technically feasible, but that in the context of an isolated, small metropolitan area, the differences in predicted land use are small.

Keywords: land use modeling; transportation modeling; *UrbanSim*; *TRANSIMS*; traffic microsimulation; accessibility

Introduction

The linkages between land use and transportation and the need to incorporate those linkages in planning are well established (Giuliano 1989, Center for Urban Transportation Studies 1999, Boarnet and Chalermpong 2001, Cervero 2003). Under the US Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 and the Transportation Equity Act for the Twenty First Century (TEA-21) of 1997 (to a lesser extent), in order to receive certain types of federal transportation funds, state or regional transportation agencies were required to model the effect of transportation infrastructure development on land-use patterns and to consider whether transportation plans and programs are consistent with land-use plans. Metropolitan Planning Organizations (MPOs) are increasingly integrating dynamic land-use modeling into those efforts to evaluate transportation infrastructure performance, investment alternatives, and air quality impacts.

Dynamic-coupled models differ from stand-alone models in that they simulate the dynamic interactions between transportation and human activities. Because

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accessibility is an important factor in determining land use, dynamic land-use models have long been integrated with four-step travel demand models (Voigt *et al.* 2009). However, as dynamic components are added to both the land-use and transportation modeling sides, model integrations become increasingly complex and difficult to implement. Little guidance exists about the optimal levels of complexity or disaggregation for modeling land use and transportation in different planning applications. The correct balance is likely to depend on the particular application of the model. Many new approaches to comprehensive model integration are being unveiled in the research community. However, as noted by Hunt *et al.* (2001), few of these models have been conclusively shown to increase the accuracy of the model output.

While ongoing work by others demonstrates the possibilities of incorporating, for instance, activity-based modeling with traffic microsimulation (Lin *et al.* 2008) and disaggregated land-use modeling with activity modeling (Waddell *et al.* 2010), this paper describes one of the first attempts to integrate a traffic router/microsimulator operations model with a highly disaggregated and dynamic land-use model.

Three components are used in this modeling effort: *UrbanSim* for land use (Waddell 2000, 2002, Waddell and Borning 2004), *TransCAD* (Caliper, Inc.) for travel demand modeling and static traffic routing and assignment, and *TRANSIMS* for dynamic traffic routing through microsimulation (Nagel and Rickert 2001, Rilett 2001). We compare the more commonly used integration of the land-use model with the static traffic assignment (i.e. *TransCAD*) to the novel integration of the land-use model with the dynamic router/microsimulator (*TRANSIMS*). The latter integration also requires use of *TransCAD* for trip generation and distribution because the *TRANSIMS* implementation is still a 'Track 1' implementation (to be described in more detail later). Given this, we refer to the simpler integration as the 'two-way model' and the more complex one as the 'three-way model'.

The models

UrbanSim is a land-use allocation model that simulates urban growth for a region based on externally derived estimates of population and employment growth (control totals). Expected growth is spatially allocated across the landscape to simulate the pattern of future development and land use. Agents in *UrbanSim* include households, employers, and real estate developers. The landscape is divided into grid cells of a user-defined size (geographic units like parcels can also be used). In this case we use 150 meter by 150 meter grid cells. Each simulated development event is assigned to one of those cells based on a utility function that incorporates factors like accessibility, site constraints, zoning, and land value. Model features include the ability to simulate the mobility and location choices of households and businesses; developer choices for quantity, location and type of development; fluxes and short-term imbalances in supply and demand at explicit locations; and housing price adjustments as a function of those imbalances.

While most other urban growth models rely on aggregate cross-sectional equilibrium predictive approaches, *UrbanSim* operates under dynamic disequilibrium, which is intended to allow for more realistic modeling of economic behavior. Supply–demand imbalances are addressed incrementally in each time period but are never fully satisfied (Iancono *et al.* 2008). In addition, *UrbanSim* endogenizes factors that older models took as exogenous, such as location of employment and the price of land and buildings. The endogenization of these factors allows them to be affected by the model as it runs.

Because accessibility is an important determinant of land use and because land use in turn affects accessibility, *UrbanSim* is generally dynamically integrated with some type of transportation model. The degree to which accessibility affects land use in a given implementation of the model system depends on the way that the various statistical sub-models in *UrbanSim* are estimated and the extent to which the data reveal a relationship. In our version of *UrbanSim*, the residential development choice location sub-model and the commercial development choice location sub-model both include significant coefficients for accessibility. Previous analysis of our two-way model suggests that accessibility has an important impact on land-use predictions. When accessibility remained constant, land-use results were found to be significantly different from when accessibility was allowed to vary (Voigt *et al.* 2009).

TransCAD is a traditional four-step travel demand model, including trip generation, trip distribution, mode split, and traffic assignment. The trip generation step quantifies the number of incoming and outgoing trips for each zone based on land use and employment patterns, and classifies these trips according to their purpose (e.g. home to work, home to shopping). Trip distribution assigns the incoming and outgoing travel from the trip generation step to specific zones. The mode split step estimates the number of trips by mode of transport. Finally, the traffic assignment identifies the route for each trip. Traffic assignment is based on an equilibrium model which employs an iterative procedure to reach convergence.

TRANSIMS is a detailed, data-intensive operations model that is designed to simulate traffic behavior with great spatial and temporal disaggregation. It consists of four modules: (1) synthetic population generator; (2) Activity Generator; (3) router; and (4) microsimulator. In stand-alone implementations, *TRANSIMS* starts by creating a synthetic population based on census and land-use data, among other data-sets. The Activity Generator then creates an activity list for each synthetic traveler. The router then computes combined route and mode trip plans to accomplish the desired activities. Finally, the microsimulator simulates the resulting traffic dynamics based on a cellular automata model, yielding detailed, second-by-second trajectories of every traveler in the system over a 24-hour period. The microsimulator allows for a highly detailed characterization of traffic flows and is able to take into account factors like queuing, car-following, and lane changing behavior. As an operations model, it is designed to model the details of signal timing and actuation and is generally not used for long-term multi-decadal predictions given that these microscopic factors are assumed to change considerably over that time scale. Currently, there is little research available on whether a microsimulator would add value to longer-term land-use predictions.

While *TRANSIMS* allows for an activity-based approach to transportation demand modeling (using the aforementioned four modules), the model's router and microsimulator modules can be applied using standard Origin–Destination (O–D) matrices. Implementing only *TRANSIMS*'s router and microsimulator is typically referred to as a 'Track 1' *TRANSIMS* implementation, and is designed to enable MPOs to take advantage of the increased resolution of the microsimulator, without having to make a significant paradigm shift toward activity-based modeling. Track 1 is the approach utilized in our implementation. A 'Track 2' implementation would also include microsimulation of activity-based travel demand. While some have suggested that using only the traffic supply modules of a microsimulator and not the traffic demand modules fails to exploit the overall purpose of disaggregate travel demand modeling (Lin *et al.* 2008), in our view the Track 1 implementation is worth exploring because we consider it is far more likely to be implemented by planning agencies, due to its lower cost of implementation and its use of familiar O–D matrices. This should in no way suggest that research into Track 2 implementation is unwarranted, however. Rather, implementation of Track 1 sets the stage for subsequent Track 2 research.

Since we have not yet incorporated *TRANSIMS* activity-based approach to transportation demand in this model system, the primary difference between the two-way model and the three-way model is the way each one characterizes traffic and resulting accessibilities (which are an input into *UrbanSim*). *TransCAD* uses a volume-delay function, where the congested travel time on the link is a function of the ratio of the number of vehicles on the link divided by the total capacity of the link. Static traffic assignment, as implemented in models such as *TRANSCAD*, also ignores the dynamic nature of traffic flow and within-the-hour variations in traffic volumes, and assumes that inflow equals outflow for all individual links in the network. As a dynamic model, *TRANSIMS*, on the other hand, calculates congested travel times based on a simulated interaction of vehicles on the roadway, taking into account factors like queuing, traffic signals, and intersection spill-back. *TRANSIMS* is designed to replicate the real-world phenomenon that leads to increased travel time and congestion that cannot be explained by just a simple volume-to-capacity ratio. This means that failure can occur at some intersections where inflow no longer equals outflow. As a result, *TRANSIMS* is likely to predict more localized bottlenecks.

Objectives

The first purpose of this paper is to introduce and describe the integration of the *TRANSIMS* router/microsimulator with the spatially disaggregated *UrbanSim* land-use model. The second purpose is to determine whether the two model integrations (i.e. the two-way and the three-way models) lead to different land-use predictions. To the extent that land-use predictions do differ, we seek to determine how differences in methods of accessibility calculations account for this. We also seek to determine whether such a long-term simulation with *TRANSIMS* results in unrealistic bottlenecks or road failures, as some contend, and if those artifacts are partly to blame for differences in land-use predictions. By characterizing and analyzing these differences we hope to shed light on the role that transportation and accessibility modeling play in long-term land-use predictions and the tradeoffs to added complexity in such modeling efforts.

Methods

Modeling site

Our models are run for Chittenden County, in the state of Vermont (VT) (Figure 1), the most populous county in the state and the home to its largest city, Burlington. Chittenden County is among the smallest metropolitan areas where *UrbanSim* has

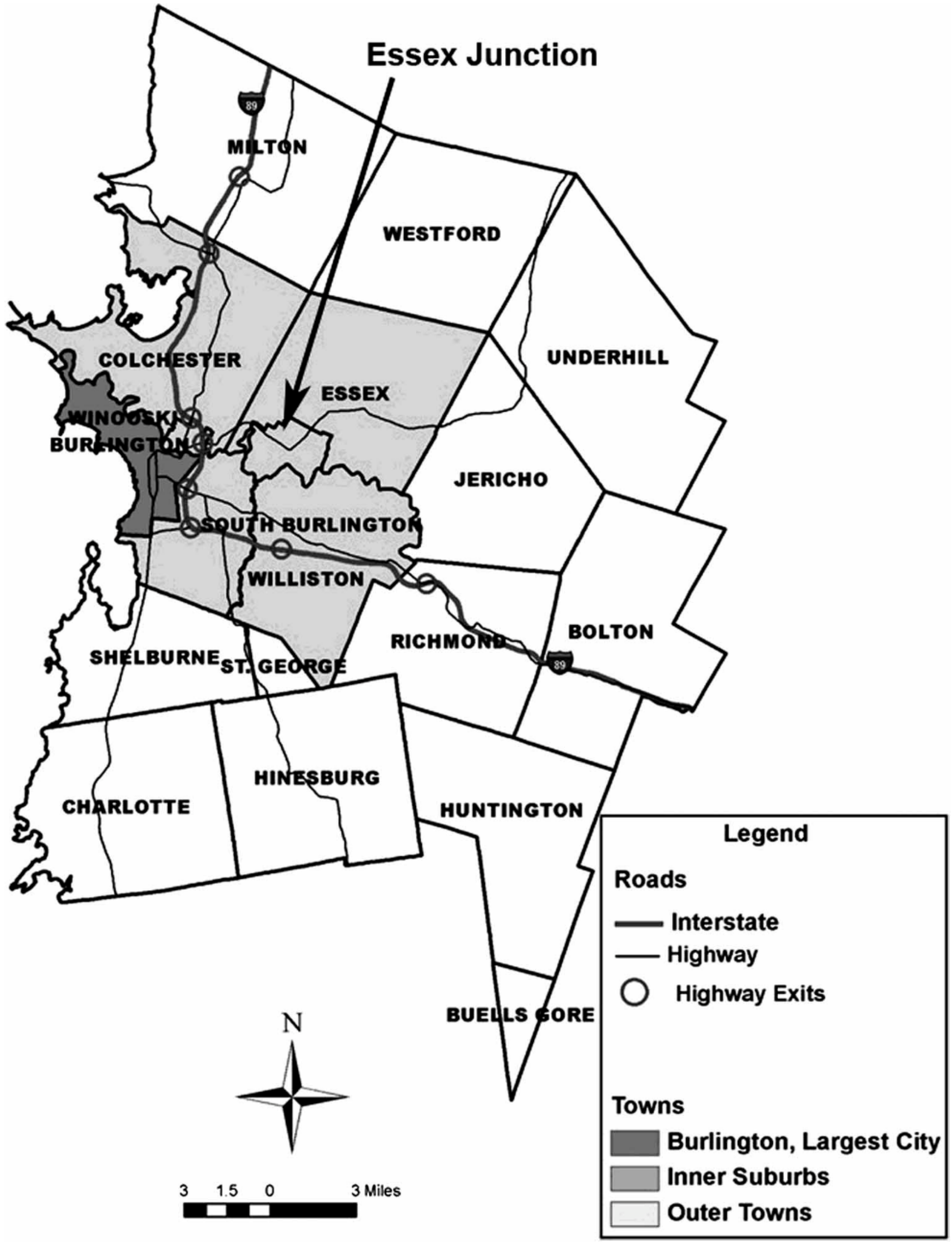

Figure 1. Map of Chittenden County.

been implemented, with an estimated 2009 population of 152,000. It is an excellent location for modeling for two reasons: first, its small size makes highly disaggregate and data-intensive modeling tractable; second, its isolation from other cities (the nearest major metropolitan area is Montreal, more than 90 miles away), means it approximates 'closed city' modeling conditions. Despite its small size, Chittenden County has its own MPO, which conducts extensive modeling.

Description of the models

This analysis was conducted by integrating previously developed implementations of the three models previously mentioned. We used an implementation of *UrbanSim* developed for Chittenden County by Troy and Voigt (Troy and Voigt 2009, Sullivan *et al.* 2010, Voigt *et al.* 2009). We used the Chittenden County Metropolitan Planning Organization's (CCMPO) implementation of *TransCAD*, which was developed for the MPO by Resource Systems Group, Inc (Resource Systems Group 2008). The model includes 335 internal traffic analysis zones (TAZs) to simulate traffic flow, and includes additional 17 external zones to represent traffic entering (or passing through) the County from outside its borders (Lawe *et al.* 2009). The travel model is based on household travel diaries collected for the CCMPO. Customized scripts were developed that automated the integrated models. We used the implementation of *TRANSIMS* developed by Resource Systems Group and Sadek (Huang *et al.* 2009, Lawe *et al.* 2009).

The two-way configuration consists of *UrbanSim*, which generates the socio-economic land-use data like total number of households and employment in each traffic analysis zone, and *TransCAD*, which derives accessibilities using travel times from the static vehicle assignment. These travel times are then sent as input to *UrbanSim*. After every five years of model time *TransCAD* is rerun using updated land-use data from *UrbanSim*, and in turn updating *UrbanSim*'s accessibilities (Troy and Voigt 2009, Voigt *et al.* 2009, Sullivan *et al.* 2010).

The three-way configuration adds a third component: the *TRANSIMS* router/microsimulator. In this configuration (Figure 2), *TransCAD* performs trip generation, trip distribution, and mode choice, and exports an afternoon (PM) peak vehicle

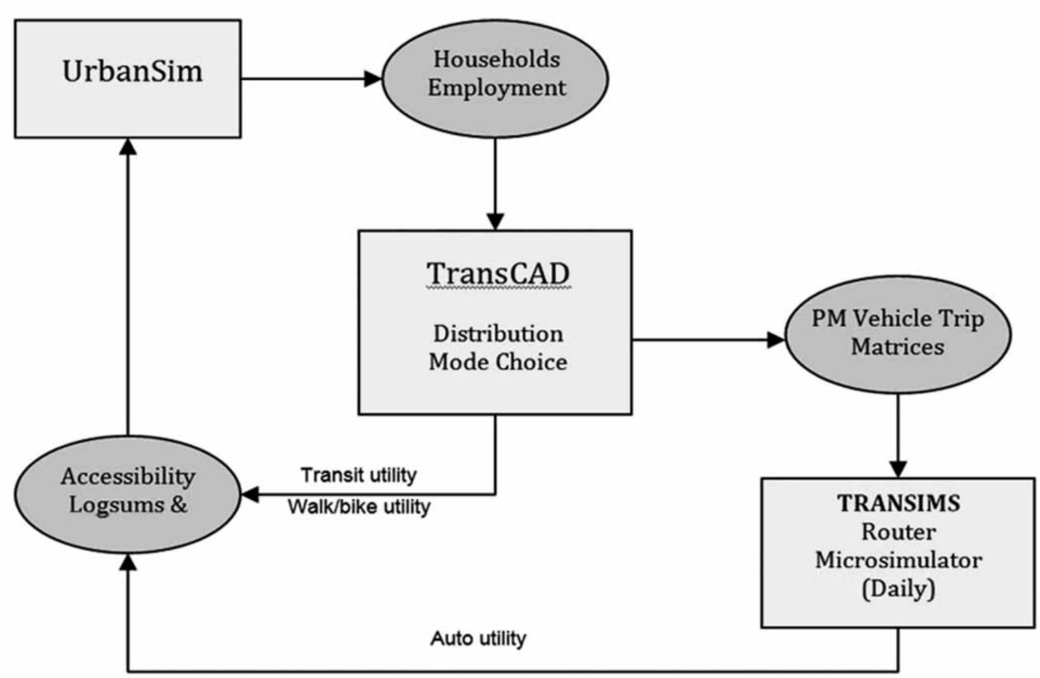

Figure 2. Three-way model configuration.

trip matrix to *TRANSIMS*. *TransCAD*'s static vehicle assignment is replaced by *TRANSIMS*' regional vehicle microsimulation. The amount and distribution of regional auto travel demand are identical in the two models, but in the three-way model accessibilities are derived using the simulation-based auto travel times and sent as input to *UrbanSim*.

Integration of the traffic microsimulation model

Because the three-way model still uses *TransCAD* for trip generation and trip distribution, and because *TransCAD* operates at an aggregate level, a significant task in integrating the three-way model was to convert the PM peak hour vehicle trip matrices produced by *TransCAD* to disaggregate trip plans that span a full 24-hour period, which could be used by the microsimulator. Using diurnal distribution data collected during the development of the daily CCMPO *TRANSIMS* model (Figure 3), and daily peak PM hour traffic volume (defined as 5:00 pm to 6:00 pm in the *TransCAD* model), we derived a PM peak hour to daily adjustment factor for each of five trip types. The calculated PM peak hour to daily adjustment factors is set forth in Troy and Voigt (2009). A macro was added to apply the daily adjustment factors to the PM peak hour CCMPO *TransCAD* model to generate daily vehicle matrices from the PM vehicle trip matrices, convert all values to integers while maintaining row totals, and export the results so they are available for input into the first module of the *TRANSIMS* model. *TRANSIMS* would then use the diurnal distributions to estimate the exact start time for each trip plan.

The second significant difference in the three-way model is the calculation of auto travel times, which are the most significant component of accessibility in the model system. In the two-way model, *TransCAD* generates a file that contains auto, walk/bike, and transit utilities as well as the logsum (composite measure of accessibility across modes) for each zone-to-zone pair. This file is fed back to *UrbanSim* for the next iteration. By incorporating *TRANSIMS* into the model chain in the three-way model, we replace the auto utilities in this file with auto utilities based

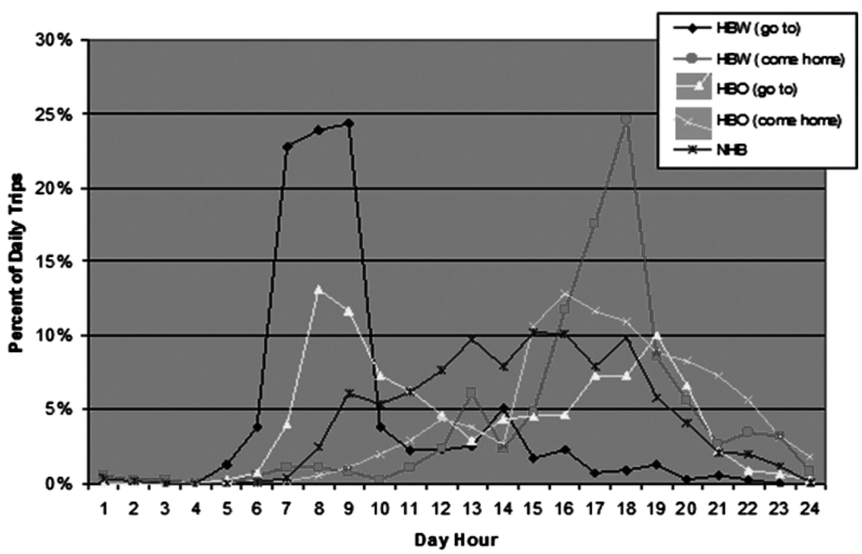

Figure 3. CCMPO *TRANSIMS* model diurnal distributions.

on zone-to-zone travel times calculated by the *TRANSIMS* microsimulator instead of the *TransCAD* model assignment module. *TRANSIMS*-based auto utilities are calculated using the following regression equation:

$$\text{Utility (Auto)} = -1.09438 - 0.020795 \times \textit{TRANSIMS}\,\text{Time}$$

Logsum values for each zone-to-zone pair are calculated based on the new auto utilities.

$$\text{Logsum} = \text{LN}(\exp[\text{Utility}(\text{Walk} - \textit{Bike})] + \exp[\text{Utility}(\text{Transist})] + \exp[\text{Utility}(\text{Auto})])$$

A python script reads the existing logsum file generated by the *TransCAD* model as well as a *TRANSIMS* zone-to-zone travel time skim file. The program updates the logsum file by calculating a new auto utility and then recalculating the logsum for each zone pair using the equations presented above. The revised logsum file can then be used as input to *UrbanSim* to complete the feedback process.

A new module was added to the CCMPO *TRANSIMS* model that creates a zone-to-zone travel time skim matrix. The skim file output contains the zone-to-zone congested travel time for the 5:00 pm to 6:00 pm hour calculated by the microsimulator.

Model runs and analysis

We ran 40-year simulations of both the two-way and three-way model integrations using the same data sets, starting in 1990 and ending in 2030. In both cases, *UrbanSim* iterated every year while the transportation model ran every five years. A fixed seed was used in choice-set delineation for *UrbanSim* to minimize stochasticity and maximize comparability between the model integrations. Both model integrations use the same *UrbanSim* model coefficients.

While a large number of indicators are produced by these model integrations, we focus this analysis on three: residential units (at the town and traffic analysis zone (TAZ) level), commercial square footage (at the town and TAZ level), and accessibilities, characterized as logsum values (at the TAZ level only). Because our model base year is 1990, we were able to conduct a preliminary validation of both model integrations against observed data from later years (2006 for household development and 2009 for commercial development). Variance ratio tests were run to look for differences in the statistical distributions of predicted future housing units and commercial square footage. Paired t-tests were run to compare differences between the two-way and three-way models for the same two indicators. These comparisons were broken down first by town and then by a coarser grouping variable which split towns into three categories: core, transitional, and non-core. Pearson's correlation coefficients were also estimated on the relationship between absolute values of town-level t-statistics from tests of difference on model predictions for land-use indicators and similar t-statistics for accessibility measures.

Results

Accuracy

Comparing model output to actual data from 2006 (residential) and 2009 (commercial, for selected towns only) at both the town and TAZ level, we found no significant differences in prediction accuracy for the two model integrations using mean absolute error and root mean square error techniques. Similarly, Pearson correlation coefficients for model outputs as compared to actual data for 2006 and 2009 revealed no significant differences in prediction accuracy.

Comparison of accessibilities

The two-way and the three-way models produced slightly different predictions of accessibility for the year 2030 (Figure 4).

The t-tests of mean-normalized logsum accessibility scores for the year 2030 indicated that there were significant differences at the 95% confidence level in 9 of the 17 towns. The towns with the highest two t-statistics (indicating greatest difference) were Essex ($t = 10.3$, $p = 0.0$) and Essex Junction ($t = 14.1$, $p = 0$).

Pearson's correlation coefficients indicated a strong relationship (Coeff. $= -0.551$, $p = 0.02$) between absolute values of town-level t-statistics from tests of difference on predicted residential units and similar t-statistics for predicted

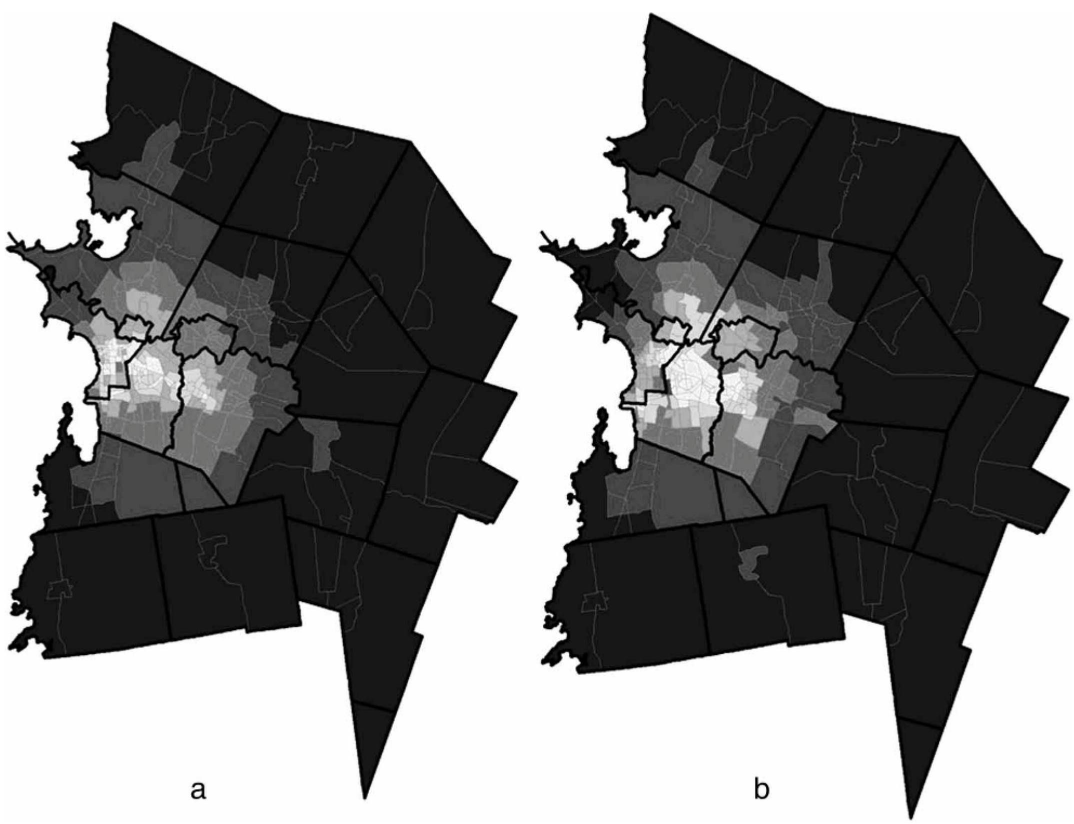

Figure 4. Comparison of accessibilities characterized as logsums by TAZ for (a) two-way model (left) and (b) three-way model (right) for the year 2030. Lighter shading indicates better accessibility; breaks between colors are based on quantile divisions.

accessibility measures. A weaker correlation (Coeff. $=0.371$, $p = -0.143$) was found when t-statistics on tests of difference for predicted commercial square footage was used instead of predicted residential units.

Comparison of land-use results

The two-way and the three-way models produced slightly different predictions of land use for the year 2030 (Figure 5). Variance ratio tests revealed no significant difference in variance across the whole population of TAZs between models for both sets of predicted indicators for 2030.

Paired t-tests at the town level for housing units indicated just one significant difference at the 95% confidence level, for the town of Essex ($t = 2.62$, $p = 0.014$), where there was an average of four more predicted housing units per TAZ under the three-way model than the two-way model. At the 90% confidence level, three additional towns had significant results: Charlotte ($t = 3.46$, $p = 0.074$), with an average of two more units predicted per TAZ for the three-way model; Milton ($t = -1.94$, $p = 0.079$), with an average of 23 fewer housing units per TAZ for the three-way model; and Essex Junction ($t = -1.86$, $p = 0.081$), with an average of nine fewer housing units for the three-way model.

When grouped by density category (core, transitional, and noncore) instead, the paired t-tests revealed no significant differences at the 95% confidence level. However, two of the three categories were significantly different at the 90% level: transitional ($t = -1.77$, $p = 0.08$), with an average of three fewer housing units per TAZ for the three-way model; and noncore ($t = 1.77$, $p = 0.082$), with an average of almost six more housing units per TAZ for the three-way model. When this analysis was run for predictions from the year 2020 instead, the transitional category became significant at the 95% confidence level ($t = -2.01$, $p = 0.046$) and the noncore category became insignificant.

Paired t-tests of the commercial square footage indicator at the town level paired indicated no significant differences at the 95% confidence level for 2030. However, there were differences at the 90% level for two towns: Essex Junction ($t = -1.94$, $p = 0.071$), with an average of 4600 fewer square feet per TAZ under the three-way model and Essex ($t = 1.88$, $p = 0.070$), with an average of 5000 more square feet per TAZ under the three-way model. When grouped by density category, nothing was significant at even the 90% confidence level.

A spatial statistical analysis was also conducted using Moran's I (Moran 1950) to see if measures of spatial autocorrelation differed between the outputs of the two models, but no difference was found.

Long-term land-use trends

We looked at graphs of key indicators to see when large discrepancies emerge between the models, if at all. As evidenced by Figure 6, the town of Milton, located far from the core of the county but with good access on the interstate, has a large and consistently growing edge in residential development under the two-way model as compared to the three-way model. Westford, a similar distance from the core, fares better under the three-way model. Most other towns do not exhibit a consistent pattern over the 40 years of the model run.

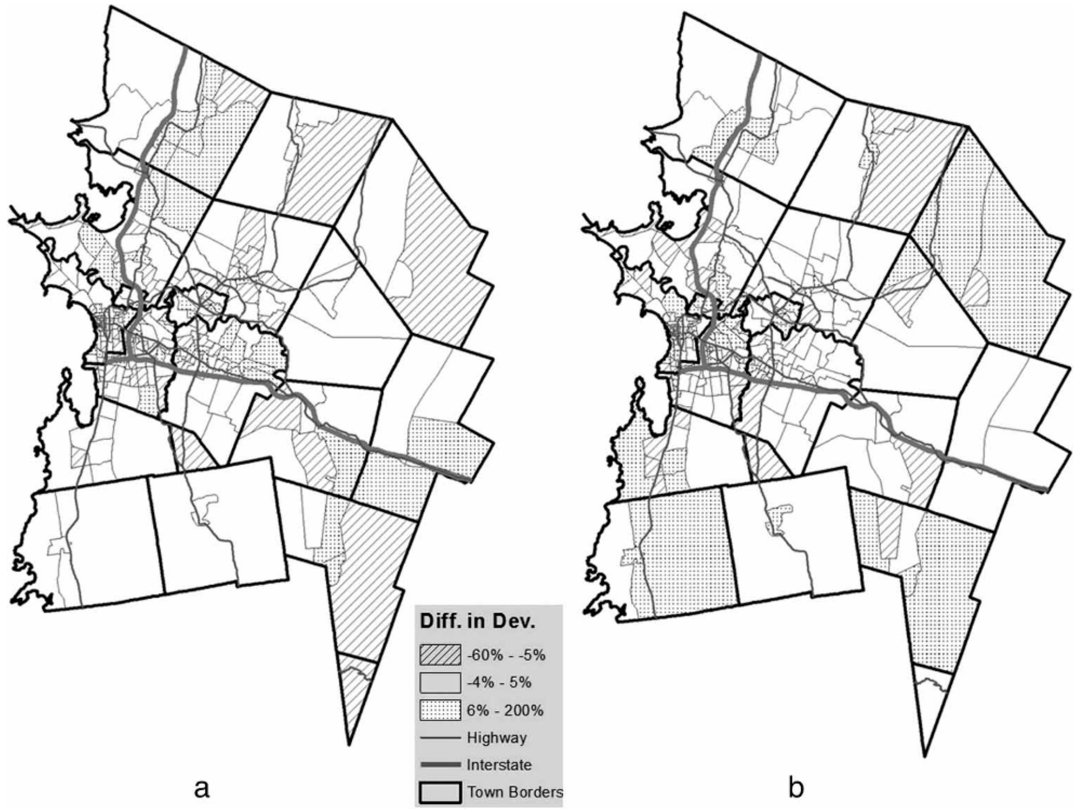

Figure 5. Differences in new (a) residential (left) and (b) commercial (right) development predicted by 2030 by the two model integrations. Cross-hatching indicates that more development is predicted by the three-way model; stippling indicates that more development is predicted by the two-way model.

Discussion

This project is one of the first known attempts to integrate a traffic router/microsimulator with a highly disaggregated and dynamic land-use model. Most importantly, it demonstrates that, although time-consuming, such an integration is feasible and that it can produce reasonable results.

Whether the integration of the microsimulator is worth the added effort for the purposes of land-use change prediction in this particular implementation is less clear-cut. With only 16 − 19 years worth of model runs to validate against observed data (and only a portion of the county in the case of commercial data), we were not expecting to find significant differences in prediction accuracies, and we did not.

The fact that accessibilities are somewhat more spatially heterogeneous in the three-way model (Figure 4) would lead us to believe that, theoretically, there could be systematic differences in the land-use outputs. Our *UrbanSim* implementation consists of 10 statistical models that drive activities like household and employment moves, land price, and development events. While many include spatial parameters such as location within the 'urban core,' or the amount of commercial or residential development within walking distance, only the residential and commercial development models include parameters on accessibility from the travel model. Because *TRANSIMS* predicted more localized areas of reduced accessibility within the interior of the county, we expected to find that some more centrally located areas might develop slightly less in the three-way model than in the two-way model. In other words, we were interested to see how sensitive both infill and peripheral development patterns might be to better representation of traffic dynamics.

Our maps of land use in 2030 (Figure 5) show just this pattern, particularly for residential development. Many of the most remote TAZs, farthest from the core and the interstate highway, have more residential development predicted by the three-way model than by the two-way model. By contrast the TAZs located near the interstate have more residential development predicted by the two-way model. This result is intuitive given what we know of the models. As population grows, *TRANSIMS* predicts more congestion and delay in the core and transitional areas, thus favoring development in the more remote TAZs. *TRANSIMS*'s link level outputs show a number of extreme traffic bottlenecks on interstate entrance and exit ramps and on local roads in the transitional area that *TransCAD* does not capture.

Correlations between the town level *t*-statistics quantifying difference in predicted land-use indicators and the difference in predicted accessibilities were statistically significant, indicating a relationship between residential unit differences and accessibility differences (less so for commercial development). Additionally, the two towns with the most significant predicted differences in terms of both commercial and residential development, Essex and Essex Junction (Figure 7), also had the biggest statistical differences in predicted accessibility. This further supports the contention that differences in accessibility are translating into

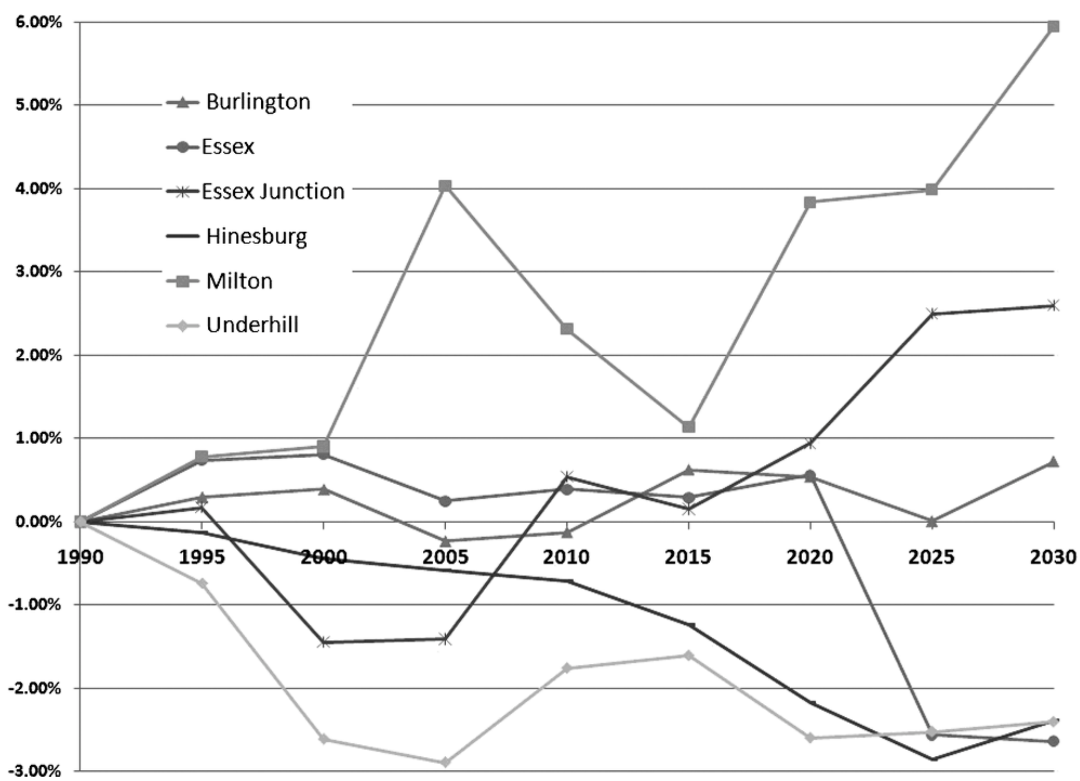

Figure 6. Percentage difference by year in predicted residential units between models for a selection of six towns. Positive numbers indicate more development in the three-way model; negative numbers indicate more development in the two-way model.

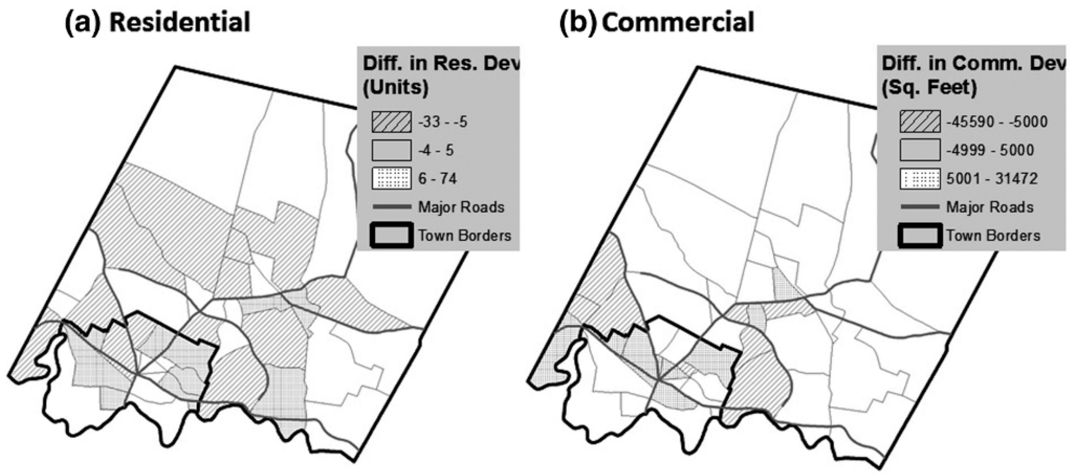

Figure 7. Blow-up of Figure 5 showing Essex and Essex Junction only. (a) Residential development (left) is measured by difference in the number of residential units predicted by the two models; (b) commercial development (right) by difference in the number of square feet of commercial development.

differences in land use. The fact that Essex Junction and Essex displayed the greatest differences is also illustrative, because these two towns include some of the most congested road bottlenecks and have some of the poorest route redundancy in the county. The fact that the two transportation models predict significantly different traffic flows in these areas suggests that a microsimulator might be particularly useful for these conditions.

The fact that differences in land use follow differences in accessibility means that both models seems to be functioning as they should. However, because the differences in accessibility are relatively small, due to the small size of the metropolitan area and its general lack of congestion, the differences in land use are similarly small. We expect that more crowded and congested metropolitan areas would exhibit more significant differences between the two model integrations.

Conclusion

TRANSIMS is designed as an operations model for assessing and optimizing microscopic factors in the traffic network. Some believe that models like this are inappropriate for coupling with long-term land-use change models. Our land-use results from the 2030 simulation look generally reasonable, but our preliminary analysis of link-level data from *TRANSIMS* indicates that after 40 years of simulation, a number of bottlenecks and congestion points develop. Whether these are unrealistic characterizations stemming from the static nature of signal timing and actuation, or reasonable predictions of future conditions is beyond the scope of this paper.

Nonetheless, these bottlenecks only had a very minor impact on development predictions. This may be because of our model coefficients, which were estimated in an area where traffic congestion is relatively minimal. Had we estimated these coefficients in a larger urban area with extensive congestion it is possible that the impacts of these accessibility differences on development would have been greater.

Hence, the impact of transportation model type on land-use results is extremely sensitive to model coefficient specification. It is also possible that had we run the *TRANSIMS* Track 2 implementation, which includes the activity model with disaggregated activity locations, differences would have been more pronounced.

Our current results suggest that integrating a microsimulator into a disaggregated land-use model leads to no obvious problems in land-use predictions, at least for the given study area type and model configuration. Nonetheless, the relatively modest differences in results suggests there is little justification for expending the extra time and resources required to implement *TRANSIMS* for the purposes of long-term land-use modeling in a context like Chittenden County. However, this approach might be more valuable in large metropolitan areas where population pressures and traffic delays are much greater. In such cases, we would expect to find delay-related (as opposed to distance-related) accessibility having a greater impact on location choice and land use. It is possible that in such cases a land-use model integrated with *TRANSIMS* would yield a more accurate characterization of accessibility, leading to better land-use predictions. However, parameters like signal timing and actualization should probably be updated regularly if a microsimulation is run for over the long term for highly congested areas. Further research is warranted to determine the usefulness of including a microsimulator in land-use modeling for more populous and congested regions as well as to determine the usefulness of adding an activity-based model.

The integration of *TRANSIMS* with a land-use model may also be valuable in assessing how hypothetical changes to the transportation network might influence the spatial pattern of development, potentially even in smaller metropolitan areas.

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References

Boarnet, M.G. and Chalermpong, S., 2001. New highways, house prices, and urban development: a case study of toll roads in orange county, CA. *Housing Policy Debate*, 12 (3), 575–605.

Center for Urban Transportation Studies, 1999. *Land use and economic development in statewide transportation planning*. US Department of Transportation, Federal Highway Administration.

Cervero, R., 2003. Growing smart by linking transportation and land use: perspectives from California. *Built Environment*, 29 (1), 66–78.

Giuliano, G., 1989. New directions for understanding transportation and land use. *Environment and Planning A*, 21 (2), 145–159.

Huang, S., *et al*., 2009. Calibrating travel demand in large-scale micro-simulation models with genetic algorithms: a TRANSIMS Model Case Study. Proceedings of the 89th Annual Meeting of the Transportation Research Board, January, Washington, DC.

Hunt, J.D., *et al.*, 2001. Comparisons from Sacramento model test bed. *Land Development and Public Involvement in Transportation*, 1780, 53–63.

Iancono, M., Levinson, D., and El-Geneidy, A., 2008. Models of transportation and land use change: a guide to the territory. *Journal of Planning Literature*, 22 (4), 323–340.

Lawe, S., *et al.*, 2009. TRANSIMS implementation in Chittenden County, Vermont: development, calibration and preliminary sensitivity analysis. *Transportation Research Record*, 2132, 113–121.

Lin, D., *et al.*, 2008. Integration of activity-based modeling and dynamic traffic assignment. *Transportation Research Record*, 2076, 52–61.

Moran, P.A., 1950. Notes on continuous stochastic phenomena. *Biometrika*, 37 (1), 17–23.

Nagel, K. and Rickert, M., 2001. Parallel implementation of the TRANSIMS micro-simulation. *Parallel Computing*, 27 (12), 1611–1639.

Resource Systems Group, 2008. *CCMPO regional transportation model documentation*. Winooski, VT: Chittenden County Metropolitan Planning Organization.

Rilett, L.R., 2001. Transportation planning and TRANSIMS microsimulation model - preparing for the transition. *Passenger Travel Demand Forecasting, Planning Applications, and Statewide Multimodal Planning*, 1777, 84–92.

Sullivan, J., *et al.*, 2010. *Integrated land-use, transportation and environmental modeling*. Burlington, VT: University of Vermont Research Report #10–006.

Troy, A. and Voigt, B., 2009. *Dynamic transportation and land use modeling: final report to USDOT FHWA.* Publication DTFH61-06-H-00022. Washington, DC: U.S. Department of Transportation.

Voigt, B., *et al.*, 2009. Testing integrated land use and transportation modeling framework. *Transportation Research Record*, 2133, 83–91.

Waddell, P., 2000. A behavioral simulation model for metropolitan policy analysis and planning: residential location and housing market components of UrbanSim. *Environment and Planning B*, 27 (2), 247–263.

Waddell, P., 2002. UrbanSim - modeling urban development for land use, transportation, and environmental planning. *Journal of the American Planning Association*, 68 (3), 297–314.

Waddell, P. and Borning, A., 2004. A case study in digital government - developing and applying UrbanSim, a system for simulating urban land use, transportation, and environmental impacts. *Social Science Computer Review*, 22 (1), 37–51.

Waddell, P., *et al.*, 2010. Microsimulating parcel-level land use and activity-based travel. *Journal of Transport and Land Use*, 3 (2), 65–84.