

Integrating UrbanSim with a traffic router and micro-simulator for transportation and land use change analysis

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1 **Abstract**

2 This paper introduces and summarizes a first-of-its-kind integration of a dynamic,
3 second-by-second traffic router/micro-simulator (TRANSIMS) with the UrbanSim land
4 use model, implemented in Chittenden County, VT. It first describes how and why these
5 components were integrated. It next describes a preliminary comparison of the land use
6 outputs of this highly complex and time-intensive model integration to a more standard
7 integration of UrbanSim with a traditional four-step transportation demand model using
8 TransCAD. Statistical tests found only slight differences in the land use predictions
9 between the two model integrations for 2030. Although these differences were slight,
10 their spatial patterns shed light on how transportation models influence the outcome of
11 land use models. In particular, differences in land use predictions appear to relate to
12 TRANSIMS' predictions of emergent traffic bottlenecks along routes that serve
13 peripheral areas where there is poor redundancy in route choice. These results suggest
14 that land use models are at least somewhat sensitive to the type of transportation model
15 that is used to generate accessibility measures. Nonetheless it is impossible to say with
16 the data at hand which is more accurate for long term predictions. It is unlikely that the
17 benefits of adding TRANSIMS or similar micro-simulators to a land use model
18 outweigh the high costs of implementation. However, this assessment may vary with
19 context. Our study site is a small metropolitan area with only modest population
20 pressures and limited traffic congestion. Our results indicate that differences in
21 predictions between model integrations grow as population forecasts are artificially
22 increased, so integration of TRANSIMS may be of greater use in more congested areas.

23 **Introduction**

24 The linkages between land use and transportation and the need to incorporate those
25 linkages in planning have been well established (1-4). Under the Intermodal Surface
26 Transportation Efficiency Act (ISTEA) of 1991 and the Transportation Equity Act for
27 the Twenty First Century (TEA-21) of 1997 (to a lesser extent), in order to receive
28 certain types of federal transportation funds, state or regional transportation agencies
29 are required to model the effect of transportation infrastructure development on land
30 use patterns and to consider whether transportation plans and programs are consistent
31 with land use plans. Metropolitan Planning Organizations (MPOs), which already
32 frequently use transportation models, are increasingly integrating dynamic land-use
33 modeling into those efforts, to help evaluate transportation infrastructure performance,
34 investment alternatives, and air quality impacts.

35 Dynamic coupled models are distinct from stand-alone models in that they simulate the
36 dynamic interactions between transportation and human activities. Because accessibility
37 largely drives land use, dynamic land use models have long been integrated with 4-step
38 travel demand models (5). However, as dynamic components are added, model
39 integrations become increasingly complex and difficult to implement. Moreover, these
40 models are generally simplistic and spatially aggregated in their characterizations of
41 traffic and accessibility. Little guidance exists about what levels of complexity or
42 disaggregation is needed or appropriate for modeling land use and transportation and
43 how that changes for different planning applications. Tradeoffs between realism and
44 cost are poorly understood. The correct balance likely depends on the particular

1 application of the model. Many new approaches to comprehensive model-integration are
2 being unveiled in the research community. However, as noted by Hunt et al. (6), few of
3 these models have been conclusively shown to increase the accuracy of the model
4 output.

5 This paper presents one of the first known attempts to integrate a traffic router/micro-
6 simulator operations model with a highly disaggregated and dynamic land use model.
7 Three components are used in this modeling effort: UrbanSim for land use (7-9),
8 TransCAD (Caliper, Inc) for travel demand modeling and traffic routing and
9 assignment, and TRANSIMS for traffic routing through microsimulation (10-11). We
10 compare the more commonly-used integration of the land use model with the static
11 traffic assignment (TransCAD) to the novel integration of the land use model with the
12 dynamic router/micro-simulator (TRANSIMS). The latter integration also requires use
13 of TransCAD for trip generation, so we refer to the simpler integration as the “2-way
14 model” and the more complex one as the “3-way model.”

15 UrbanSim is a land-use allocation model that simulates urban growth for a region based
16 on externally derived estimates of population and employment growth (control totals).
17 Expected growth is spatially allocated across the landscape to simulate the pattern of
18 future development and land use. Agents in UrbanSim include both households and
19 employers. The landscape is divided into grid cells of a user-defined size (geographic
20 units like parcels can also be used). Each simulated development event is assigned to
21 one of those cells based on factors like accessibility, site constraints, and zoning. While
22 almost all other urban growth models rely on aggregate cross-sectional equilibrium
23 predictive approaches, UrbanSim is an agent-based behavioral simulation model that
24 operates under dynamic disequilibrium, which allows for more realistic modeling of
25 economic behavior; supply-demand imbalances are addressed incrementally in each
26 time period but are never fully satisfied. Because of its dynamic nature, UrbanSim can
27 endogenize factors that other models take as exogenous, such as location of
28 employment and the price of land and buildings. Model features include the ability to
29 simulate the mobility and location choices of households and businesses; developer
30 choices for quantity, location and type of development; fluxes and short-term
31 imbalances in supply and demand at explicit locations; and housing price adjustments
32 as a function of those imbalances. Because accessibility is such a core determinant of
33 land use, UrbanSim is generally integrated with some type of transportation model. The
34 assumption is that accessibility changes over time so transportation must be made
35 endogenous. The degree to which accessibility affects land use depends on the way that
36 the various statistical models in UrbanSim are parameterized and the extent to which
37 the data reveals a relationship. In our version of UrbanSim, we estimated a number of
38 models, several of which include coefficients for accessibility.

39 TransCAD is a traditional four-step travel demand model, including trip generation, trip
40 distribution, mode split and traffic assignment. The trip generation step quantifies the
41 number of incoming and outgoing trips for each zone based on land use and
42 employment patterns, and classifies these trips according to their purpose (e.g., home to
43 work, home to shopping). Trip distribution assigns the incoming and outgoing travel
44 from the trip generation step to specific zones. The mode split step estimates the

1 number of trips by mode of transport. Finally, the traffic assignment identifies the route
2 for each trip. Traffic assignment is based on an equilibrium model which employs an
3 iterative procedure to reach convergence.

4 TRANSIMS is a detailed, data-intensive operations model that is designed to simulate
5 traffic behavior with great spatial and temporal disaggregation. It consists of four
6 modules: (1) synthetic population generator; (2) activity generator; (3) router; and (4)
7 micro-simulator, although in this case we use only the third and fourth components. In
8 standalone implementations, TRANSIMS starts by creating a synthetic population based
9 on census and land use data, among other data sets. The Activity Generator then
10 creates an activity list for each synthetic traveler. The activity generator and the router
11 then compute combined route and mode trip plans to accomplish the desired activities.
12 Finally, the micro-simulator simulates the resulting traffic dynamics based on a cellular
13 automata model, yielding detailed, second-by-second trajectories of every traveler in
14 the system over a 24-hour period. The micro-simulator allows for a highly detailed
15 characterization of traffic flows and is able to take into account factors like cueing, car-
16 following, and lane changing behavior. As an operations model, it is designed to help
17 optimize microscopic factors such as signal timing and actuation.

18 While TRANSIMS allows for an activity-based approach to transportation demand
19 modeling (using its population synthesizer and activity generator), the model's router
20 and micro-simulator modules can still be applied using standard Origin-Destination (O-
21 D) matrices. This provides a cost-effective approach for regional planning
22 organizations, which can take advantage of the increased resolution of the TRANSIMS
23 micro-simulator, while continuing to depend upon familiar O-D matrices.
24 Implementing only TRANSIMS's router and micro-simulator is typically referred to as
25 a "Track 1" TRANSIMS implementation. "Track 1" TRANSIMS implementation has
26 been the focus of the current work so far.

27 The primary difference between TransCAD and TRANSIMS is the way each one
28 characterizes traffic and resulting accessibilities (which are an input into UrbanSim).
29 TransCAD uses a volume-delay function, where the congested travel time on the link is
30 equal to the ratio of the number of vehicles on the link divided by the total capacity of
31 the link. It assumes that inflow equals outflow for all individual links in the network.
32 TRANSIMS, on the other hand, calculates congested travel times based on a simulated
33 interaction of vehicles on the roadway that takes into account factors like weaving,
34 merging, queuing, traffic signals, and intersection spill-back. TRANSIMS is designed
35 to replicate the real-world phenomenon that lead to increased travel time and congestion
36 that cannot be explained by just a simple volume-to-capacity ratio. This means that
37 failure can occur at some intersections where inflow no longer equals outflow. As a
38 result, TRANSIMS is likely to predict more localized bottlenecks.

39

40

1 **Objectives**

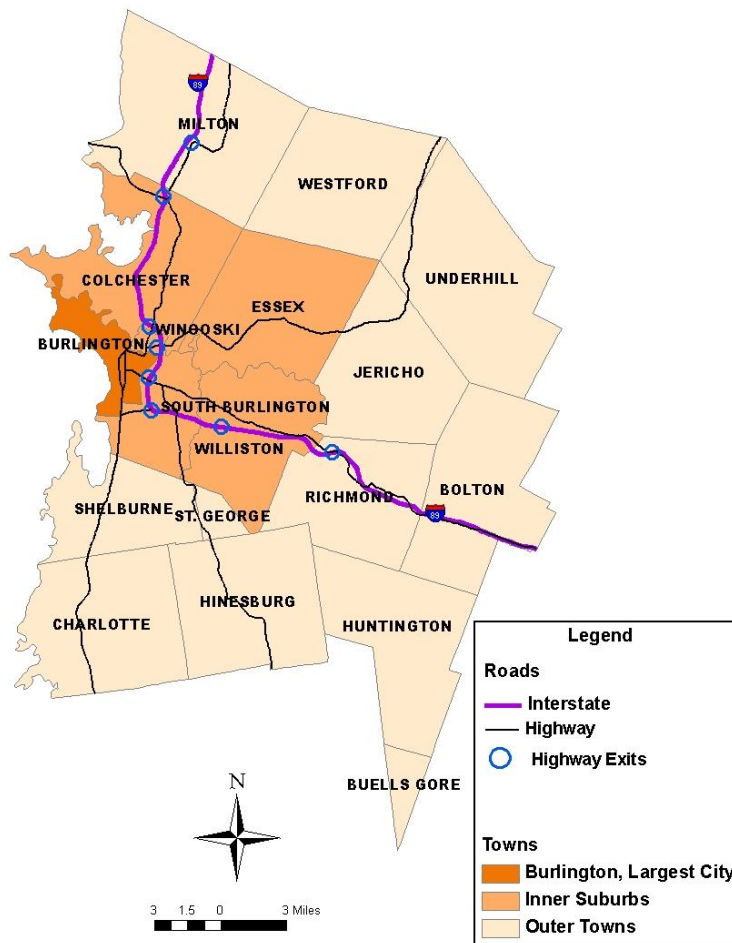
2 The first purpose of this paper is to introduce and describe the first-of-its-kind
3 integration of the TRANSIMS router/micro-simulator with the UrbanSim land use
4 model. The second purpose is to determine whether the two model integrations lead to
5 different land use predictions. To the extent the land use predictions differ, we analyze
6 the pattern of outputs to better understand how the two approaches to calculating
7 accessibilities in each transportation model contributes to these differences. By
8 characterizing and analyzing these differences we hope to shed light on the role that
9 transportation and accessibility modeling play in long-term land use predictions and the
10 tradeoffs to added complexity in such modeling efforts.

11

12 **Methods**

13 Modeling Site

14 Our models are run for Chittenden County, VT (Figure 1), the most populous county in
15 the state and the home to its largest city, Burlington. Chittenden County is among the
16 smallest metropolitan areas where UrbanSim has been implemented, with an estimated
17 2009 population of 152,000. It is an excellent location for modeling for two reasons:
18 first, its small size makes highly disaggregate and data-intensive modeling tractable;
19 second, its isolation from other cities (the nearest metropolitan area is Montreal, more
20 than 90 miles away), means it approximates “closed city” modeling conditions
21 (although we do use 17 external TAZs to account for inter-county traffic, this is a small
22 component of the county’s overall transportation). Despite its small size, Chittenden
23 County has its own Metropolitan Planning Organization, which conducts extensive
24 modeling.



1
 2 **FIGURE 1 Map of Chittenden County.**

3 Description of the Models

4 This analysis was conducted by integrating previously developed implementations of
 5 three models. We used the implementation of TRANSIMS developed by Resource
 6 Systems Group and Adel Sadek (12, 13). We use an implementation of UrbanSim
 7 developed for the same area by Austin Troy and Brian Voigt (6, 14, 15). We used the
 8 Chittenden County Metropolitan Planning Organization’s (CCMPO) implementation of
 9 TransCAD, which was developed for the MPO by Resource Systems Group, Inc. The
 10 model includes 335 internal traffic analysis zones (TAZs) to simulate traffic flow, and
 11 includes an additional 17 external zones to represent traffic entering (or passing
 12 through) the County from outside its borders (14). The travel model is based on
 13 household travel diaries collected for the CCMPO. Customized scripts were developed
 14 that automated the integrated models.

15 The 2-way configuration consists of UrbanSim, which generates the socio-economic
 16 land use data like total number of households and employment in each traffic analysis
 17 zone, and TransCAD, which derives accessibilities using travel times from the static
 18 vehicle assignment. These travel times are then sent as input to UrbanSim. After every

1 five years of model time TransCAD is rerun using updated land use data from
2 UrbanSim, and in turn updating UrbanSim's accessibilities for that model component
3 (6, 14, 15).

4 The 3-way configuration adds a third component: the TRANSIMS router/micro-
5 simulator. In this configuration (Figure 2), TransCAD performs trip generation, trip
6 distribution, and mode choice, and exports a PM peak vehicle trip matrix to
7 TRANSIMS. TransCAD's static vehicle assignment is replaced by TRANSIMS'
8 regional vehicle micro-simulation. The amount and distribution of regional auto travel
9 demand is identical in the two models, but in the 3-way model the auto travel times are
10 derived from the regional micro-simulation. Finally, accessibilities are derived using
11 the simulation-based auto travel times and sent as input to UrbanSim.

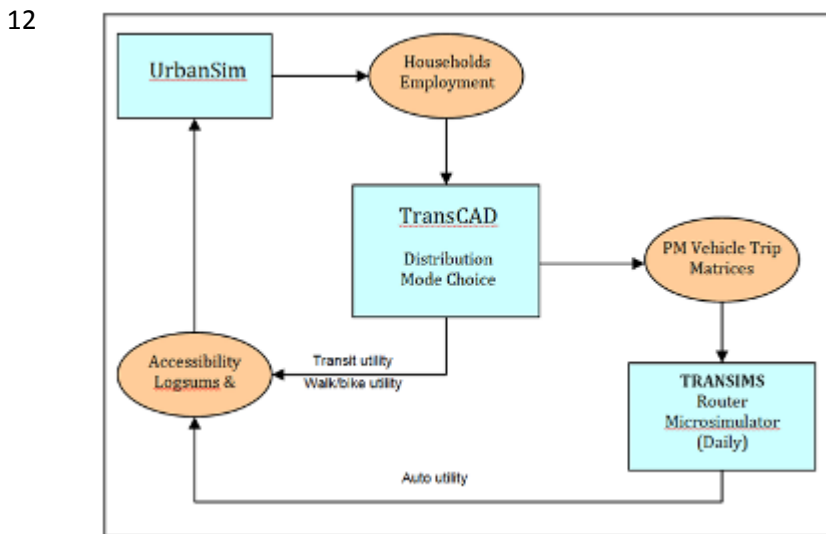


FIGURE 2 Three-way model configuration.

13

14 Conversion of PM Vehicle Trip Matrices

15 To integrate the CCMPO PM-peak hour TransCAD model and the daily CCMPO
16 TRANSIMS model we first needed to convert the PM peak hour vehicle trip matrices
17 produced by TransCAD to daily vehicle trips.

18 There are five post-mode-choice vehicle trip matrices for three trip purposes: (1) home-
19 based-other, leaving home; (2) home-based-work, coming home; (3) home-based-other,
20 coming home; (4) home-based-work, work to nonhome; and (5) non-home-based,
21 nonwork to nonhome. There is also a single post-distribution trip table which includes
22 commercial truck trips. Finally, there is a single post-distribution trip table which
23 includes external-to-external trips.

24 We had diurnal distribution data that was collected during the development of the daily
25 CCMPO TRANSIMS model, and daily peak PM hour traffic volume (defined as 5:00
26 pm to 6:00 pm in the TransCAD model). From this, we derived a PM peak hour to daily
27 adjustment factor for each trip type using the diurnal distribution data. The diurnal

1 distribution data is presented in Figure 3 below. The calculated PM peak hour to daily
 2 adjustment factors are set forth in Troy, et al. (14).

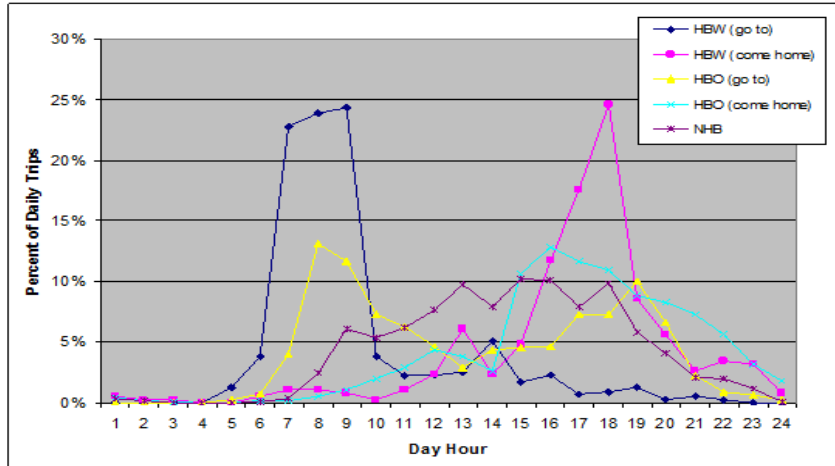


FIGURE 3 CCMPO TRANSIMS model diurnal distributions.

3
 4 A new macro was added to the PM-peak hour CCMPO TransCAD model that applies
 5 the adjustment factors to the PM vehicle trip matrices to generate daily vehicle
 6 matrices. The macro then exports the vehicle trip matrices for each trip type as comma-
 7 delimited text files. A custom Visual Basic program then applies a bucket rounding so
 8 row totals are maintained since the number of trips for each origin-destination pair must
 9 be in integer form for input to TRANSIMS. The trip lists for each trip type are now
 10 ready for input into the ConvertTrips batch which is the first module of the TRANSIMS
 11 model.

12

13 Updating the Accessibility File with TRANSIMS Times

14 For the 2-way model, TransCAD generates a file that contains the auto, walk/bike, and
 15 transit utilities as well as the logsum (composite measure of accessibility across modes)
 16 for each zone-to-zone pair. This file is fed back to UrbanSim for the next iteration. By
 17 incorporating TRANSIMS into the model chain in the 3-way model, we replace the auto
 18 utilities in this file with auto utilities based on zone-to-zone travel times calculated by
 19 the TRANSIMS micro-simulator instead of the TransCAD model assignment module.

20 TRANSIMS-based auto utilities are calculated using the following regression equation:

21
$$\text{Utility (Auto)} = -1.09438 - 0.020795 * \text{TRANSIMS Time}$$

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

23
$$\text{Logsum} = \text{LN}(\text{EXP}[\text{Utility}(\text{Walk-Bike})] + \text{EXP}[\text{Utility}(\text{Transit})] + \text{EXP}[\text{Utility}(\text{Auto})])$$

1 TRANSIMS has built-in utilities that aggregate the temporally and spatially detailed
2 travel time information produced by the vehicle microsimulation to produce zone-to-
3 zone congested travel time skim matrices for selected time periods and increments. A
4 new module was added to the TRANSIMS model to produce and save these zone-to-
5 zone travel time skim matrices. The skim file output contains the zone-to-zone
6 congested travel time for the 5:00pm to 6:00pm hour calculated by the micro-simulator,
7 since the 2-way model also utilized PM peak hour travel times from the static vehicle
8 assignment.

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

14 A new module was added to the CCMPO TRANSIMS model that writes out a zone-to-
15 zone travel time skim matrix. The skim file output contains the zone-to-zone congested
16 travel time for the 5:00pm to 6:00pm hour calculated by the micro-simulator.

17 Model Runs and Analysis

18 We ran forty year simulations of both the 2-way and 3-way model integrations using the
19 same data sets, starting in 1990 and ending in 2030. In both cases, UrbanSim iterated
20 every year while the transportation model ran every five years. A fixed seed was used in
21 choice-set delineation for UrbanSim to minimize stochasticity and maximize
22 comparability between the model integrations. Each model integration uses the same
23 UrbanSim model coefficients.

24 Two versions of each model were run, one using population and employment forecasts
25 obtained from the MPO as control totals, known as the “baseline scenario,” and another
26 using controls totals artificially increased by 50%, known as the “increased control total
27 scenario.” This was done to help determine whether differences in the models may
28 relate to population development pressures.

29 Finally, we analyzed the outputs. While a large number of indicators are produced by
30 these model integrations, we focus this analysis on three: residential units (at the town
31 and TAZ level), commercial square footage (at the town and TAZ level) and
32 accessibilities, characterized as logsum values (at the TAZ level only). Because our
33 model base year is 1990, we were able to conduct a preliminary validation of both
34 model integrations against observed data from later years (2006 for household
35 development and 2009 for commercial development). We found no statistically
36 significant differences in prediction accuracies for the two model integrations. For that
37 reason, we do not present the results here. Nevertheless, we ran statistical analyses to
38 look for differences in the 2030 outputs of the two models and analyzed geographic
39 patterns in those differences.

40

41

1 **Results**

2 Statistical differences in models

3 Variance ratio tests for the whole population of TAZs revealed no significant difference
4 in variance across the whole population of TAZs between models for both sets of
5 indicators for 2030. Using paired t-tests, slight significant differences were found in
6 predicted commercial square footage for 2030 at the TAZ level when grouped by town.
7 For the baseline population scenario, significant differences in commercial square
8 footage were found at the 95% confidence level for the town of Williston ($t=2.654$,
9 $p=0.011$), which has the third largest number of TAZs in the county. Westford had
10 significant differences at the 90% confidence level ($t=-2.366$, $p=0.099$). With the
11 increased control total scenario, differences were fewer: there were no significant
12 differences in commercial square footage at the 95% confidence level, although
13 Burlington ($t=-1.825$, $p=0.072$) and Shelburne ($t=-1.867$, $p=0.92$) were different at the
14 90% level. A significant difference in residential units was found for Milton at the 95%
15 confidence level in the baseline scenario ($t=-2.487$, $p=.03$). In the increased control
16 total scenario, significant differences at the 95% level were found in residential units
17 for Jericho ($t=-3.61$, $p=.037$) and at the 90% level for Milton ($t=-2.12$, $p=.058$). A
18 spatial statistical analysis was also conducted using Moran's I (Moran (1950) to see if
19 measures of spatial autocorrelation differed between the outputs of the two models, but
20 no difference was found.

21

22 Preliminary Comparison of Travel Times

23 Figure 4 shows the difference in predicted logsum accessibilities between TRANSIMS
24 and TransCAD for the year 2030 under a scenario with baseline population forecast
25 control totals. Because accessibility is one of the core driving factors in the land use
26 predictions, the fact that there are clear differences in the spatial pattern of accessibility
27 served as an indication that differences in land use outputs were a distinct possibility
28 and that further analysis was warranted.

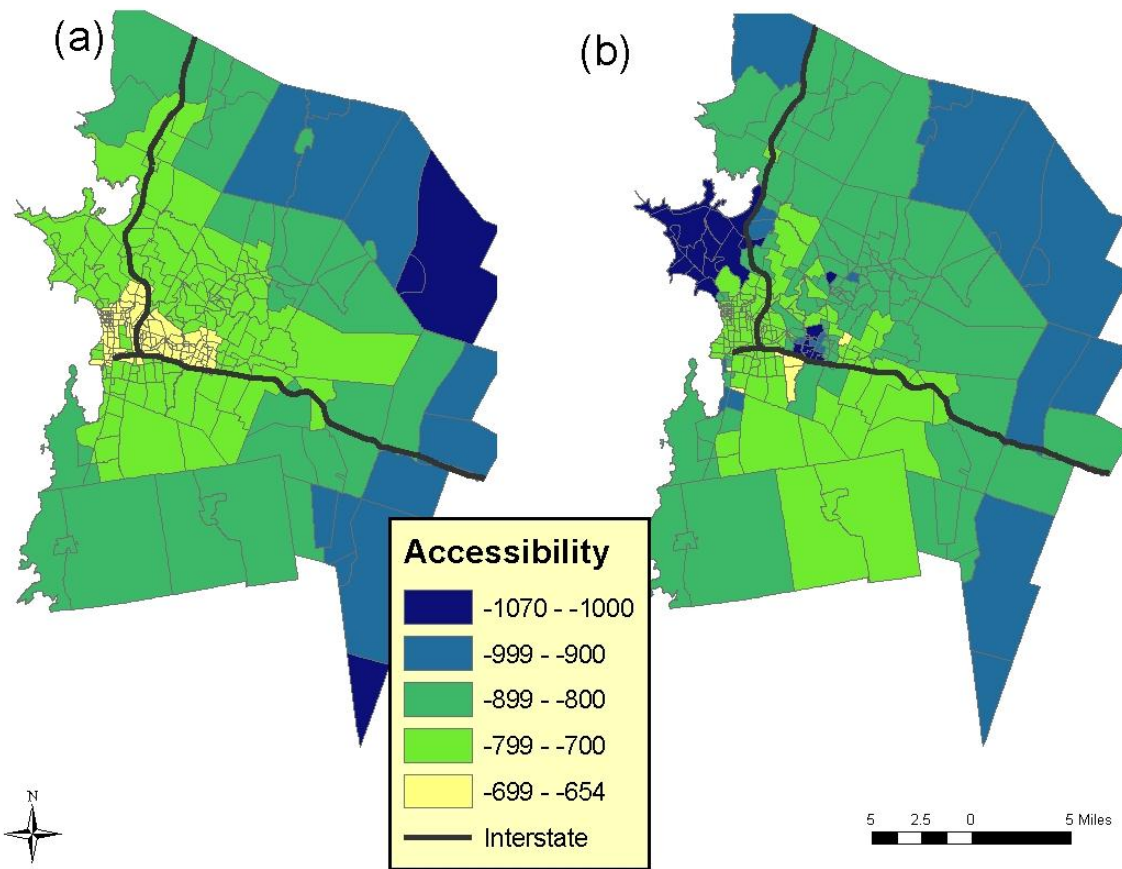
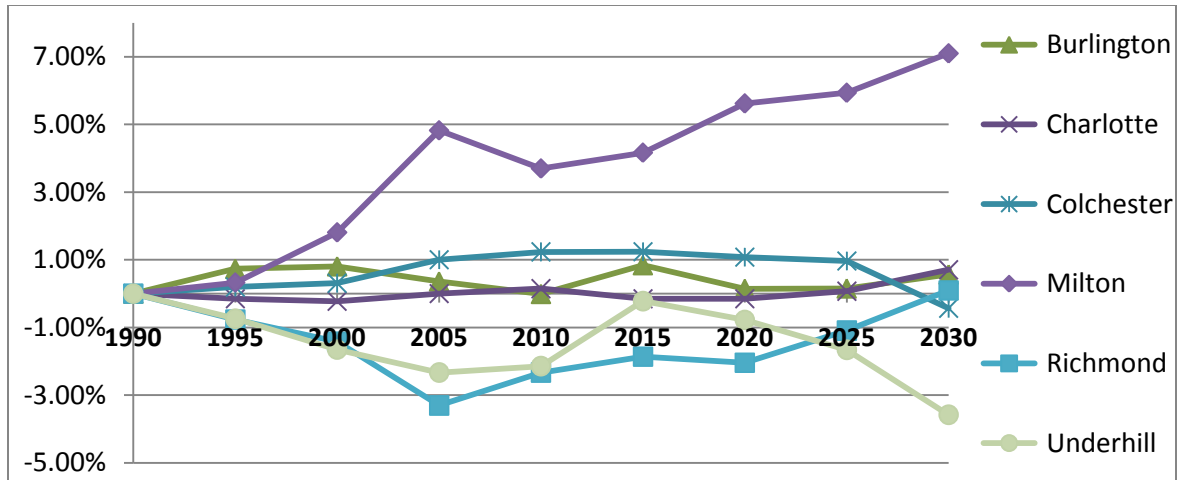


FIGURE 4 Comparison of accessibilities characterized as logsums by TAZ for 2-way (a) and 3-way (b) models. Logsums are unitless measures of relative accessibility. Yellow indicates TAZs with better accessibility, blue indicates worse.

1

2 Long-term trends

3 We looked at graphs of key indicators to see when large discrepancies emerge between
 4 the models, if at all. Figure 5 shows the percent difference in predicted housing units
 5 between the two models for a sample of eight towns from 1990 to 2030. It indicates a
 6 continuously growing difference for the outlying towns of Milton and Underhill. Milton
 7 has higher predictions for the 2-way model, while Underhill has the opposite. Other
 8 towns, like Bolton, show divergence between the models in early years and then return
 9 to smaller differences later. Several towns start to show patterns of divergence between
 10 models and then return to small differences in later years, such as South Burlington,
 11 Richmond and Colchester. Others are in close agreement throughout all forty years of
 12 model time, such as Charlotte and Burlington. Commercial square footage prediction
 13 graphs (not shown here) show a somewhat similar pattern with Milton also having
 14 increasingly positive 2-way prediction differences over time, several outlying towns
 15 with the opposite pattern and a number of towns in the middle, with relatively little
 16 difference.



1
 2 **FIGURE 4** Percent difference in predicted residential units between models (2-way
 3 minus 3-way divided by total units) for a sample of 6 towns.

4 Side by side maps in Figure 6 and 7 show percentage differences in predicted
 5 residential units (a) and commercial square footage (b) for 2030 at the town level and
 6 the TAZ level, respectively, under the increased control total scenario. Baseline control
 7 total maps are not shown in the interests of space and because the patterns are similar
 8 but much weaker.

9

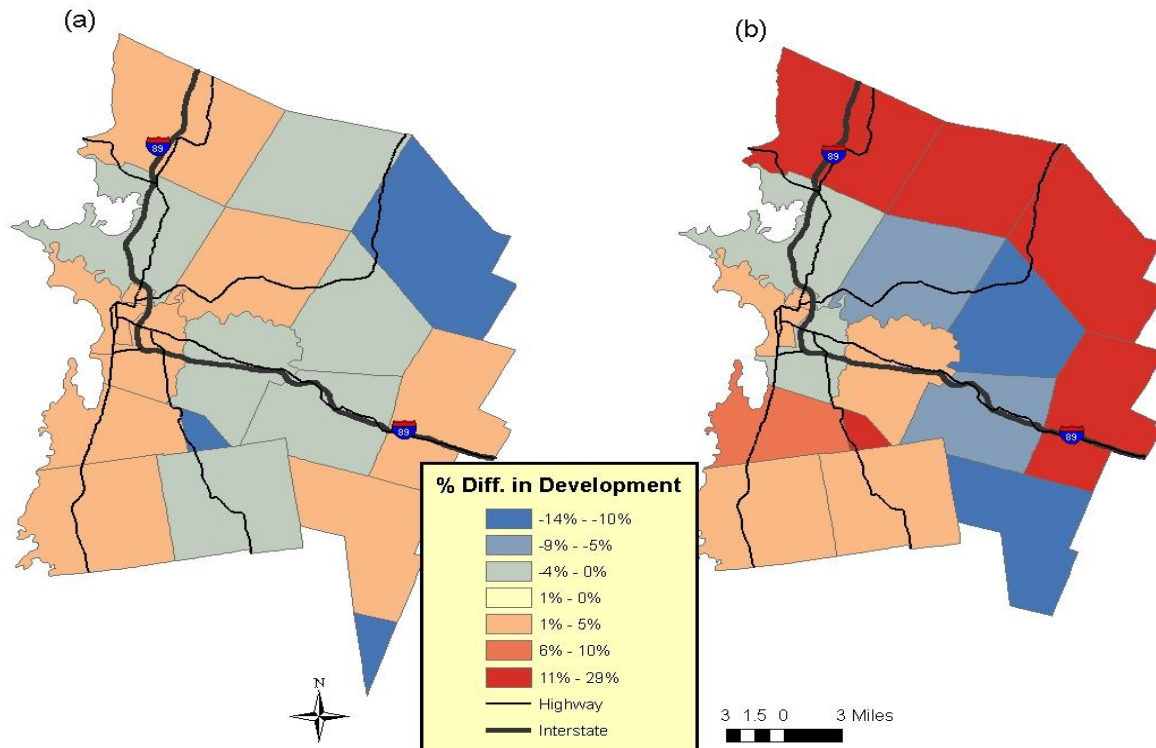
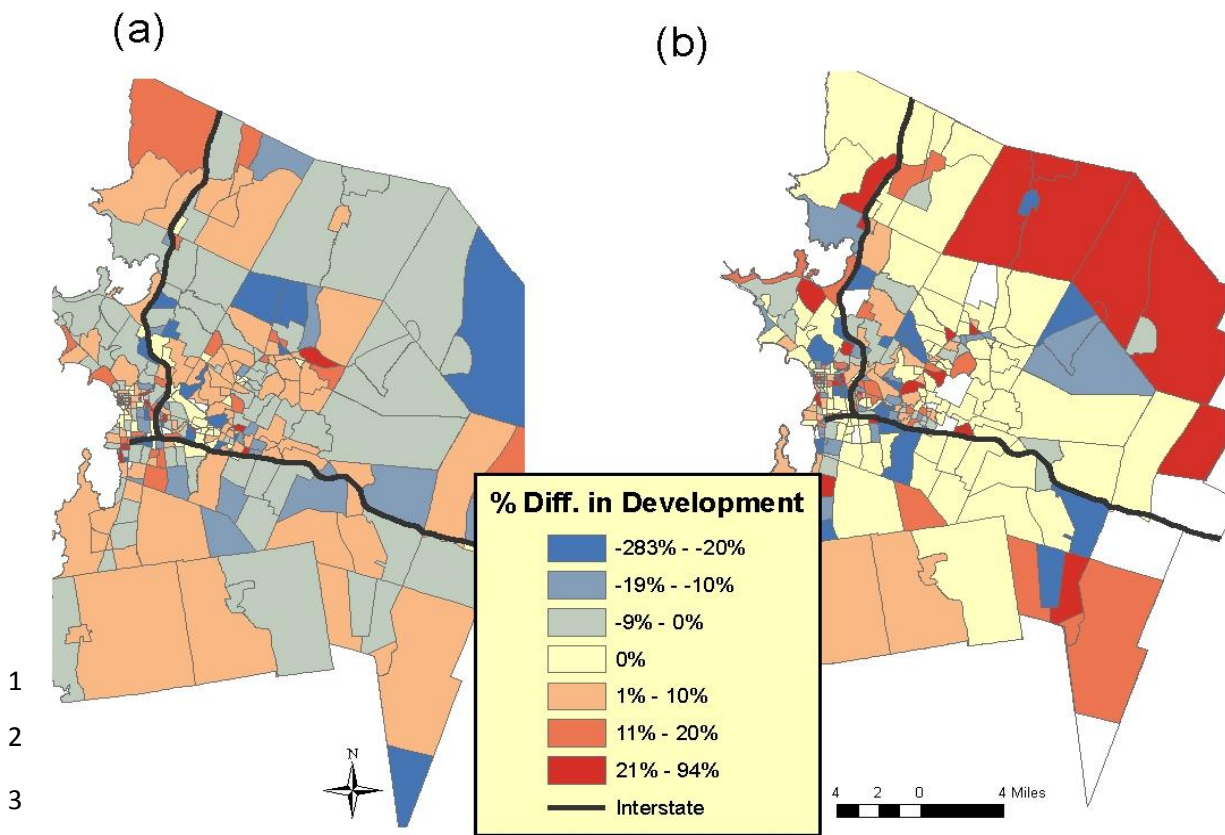


FIGURE 5 Town-level comparison under increased control totals: (a) Percent
 difference in residential development forecasts from the two way and three-way models
 for 2030 using baseline control totals. (b) Percent difference in commercial
 development forecasts from the two way and three-way models for 2030 using baseline
 control totals. Blue indicates more development predicted by the three-way model; red
 indicates more development predicted by the two-way model.



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FIGURE 6 Same as Figure 6 but at the TAZ level.

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Discussion

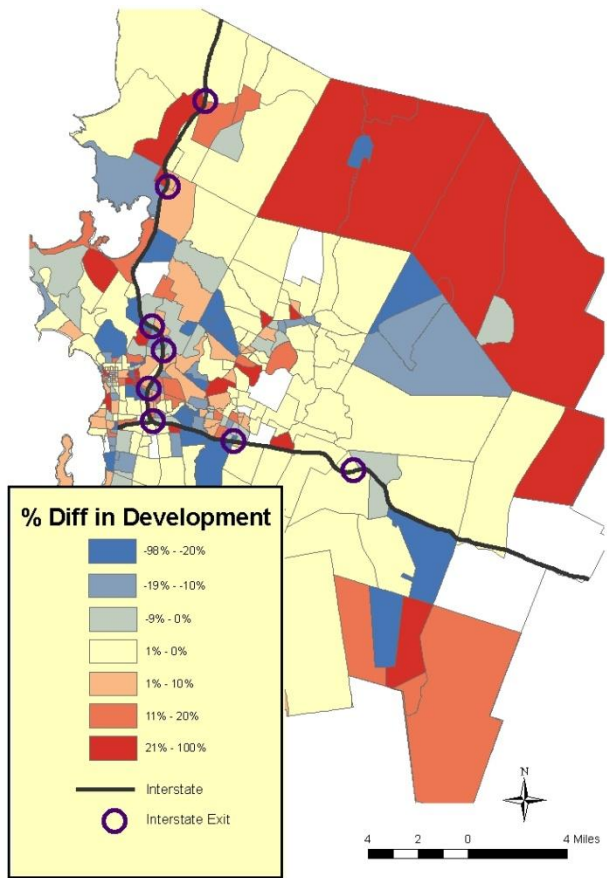
8 This project was the first of its kind to successfully integrate the TRANSIMS
 9 router/micro-simulator with a highly disaggregated and dynamic land use model like
 10 UrbanSim. This project is significant in showing that such an integration of highly
 11 complex models is feasible. However, questions remain about whether using this type
 12 of transportation model has significant implications for land use modeling or not and, if
 13 so, whether its benefits are worth the effort. With hundreds of gigabytes of outputs, far
 14 more analysis of the results of these models remains to be done before an answer to
 15 these questions can be made definitely. However, this analysis represents a preliminary
 16 attempt to address it.

17 The fact that accessibilities are far more spatially heterogeneous in the 3-way model
 18 (Figure 4), would lead us to believe that, theoretically, there could be systematic
 19 differences in the land use outputs. Our UrbanSim implementation consists of ten
 20 statistical models that drive activities like household and employment moves, land

1 price, and development events. While many include spatial parameters such as location
2 within the “urban core,” or the amount of commercial or residential development within
3 walking distance, only the residential and commercial development models include
4 parameters on accessibility from the travel model. Because TRANSIMS predicted more
5 localized areas of reduced accessibility within the interior of the county, we expected to
6 find that some more centrally located areas might develop slightly less in the 3-way
7 model than in the 2-way model.

8 While the results of our two models are different, it is not clear that these differences
9 are important enough to matter for the purposes of land use change prediction. Our
10 validation results (not presented here) show minimal differences between the two in
11 predicting intermediate-year data. Statistical pairwise comparisons of TAZ-level results
12 grouped by town suggest that differences in predicted indicators for 2030 are present
13 for only a few towns. Tests of the whole population of TAZs found no significant
14 difference in variance for both land use indicators.

15 Nonetheless, our maps of 2030 prediction differences in commercial development under
16 increased control totals (which was use because it emphasizes the differences between
17 models more) show some interesting patterns that suggest potential systematic spatial
18 differences in predictions. As Figure 6 shows, all the peripheral towns along the
19 northern and eastern boundaries of the county have more commercial development
20 under the 2-way model than under the 3-way. The same pattern is evident at the TAZ
21 level, although heterogeneity is slightly greater along the periphery. This result is
22 intuitive given what we know of the models. As population grows, TRANSIMS predicts
23 more congestion and delay and hence lesser accessibility in the outer TAZs than
24 TransCAD. This pattern is particularly evident for TAZs that do not adjoin the
25 Interstate (where the Interstate runs through, there are fewer red TAZs). Redundancy of
26 routes is very poor the further out one travels in the county, so just a few high-delay
27 links can make a big impact on accessibility in areas that require a long drive on non-
28 Interstate routes. Our preliminary analysis of TRANSIMS’s link level outputs (not
29 presented here) shows a number of predicted traffic bottlenecks along such key arterials
30 that connect outer suburbs to the urban core that TransCAD does not capture. Not all of
31 these “red TAZs” are on the outer periphery. Some are more central, but require
32 significant driving on bottleneck-prone arterials. Interestingly, as is reflected in Figure
33 8, most of the TAZs containing an Interstate exit appear to have higher employment
34 predictions in the 2-way model, which is consistent with this explanation.



1

2 **FIGURE 8 Blow-up of Figure 7(b) showing Interstate Exits.**

3

4 No clear spatial pattern is evident for differences in residential predictions. Figure 6
 5 suggests that only one of the towns included in the graph experience steadily increasing
 6 differences over time between models. Otherwise, differences oscillated within a small
 7 range over time. This difference between residential and commercial indicators is likely
 8 due to the model coefficients that relate to output from the transportation models. The
 9 residential developer model includes a parameter for home accessibility to employment
 10 while the commercial developer model includes a parameter for work accessibility to
 11 employment. Further, the commercial development coefficient is almost twice the
 12 magnitude of the residential coefficient.

13

14 **Conclusion**

15 TRANSIMS is designed as an operations model for assessing and optimizing
 16 microscopic factors in the traffic network. Some believe that models like this are
 17 inappropriate for coupling with long-term land use change models. Our land use results
 18 from the 2030 simulation look generally reasonable, but our preliminary analysis of link
 19 level data from TRANSIMS indicates that after forty years of simulation, a number of

1 unrealistic bottlenecks and congestion points develop. This is probably because, as an
2 operations model, TRANSIMS runs with an assumption that factors like signal timing
3 and lane rules are to be changed over time. When they remain static over long periods
4 like forty years, this may lead to unrealistic characterizations of accessibility.
5 Nonetheless, these bottlenecks only had a very minor impact on development
6 predictions. This may be because of our model coefficients, which were estimated in an
7 area where traffic congestion is relatively minimal. Had we estimated these coefficients
8 in a larger urban area with extensive congestions, it is possible that the impacts of these
9 accessibility differences on development would have been greater. Hence, the impact of
10 transportation model type on land use results is extremely sensitive to model coefficient
11 specification. It is also possible that had we run the TRANSIMS Track 2
12 implementation which includes the activity model with disaggregated activity locations,
13 differences would have been more pronounced.

14 Given our current results, there appears to be little justification for expending the large
15 amount of time and money required to implement TRANSIMS for the purposes of long-
16 term land use modeling in a context like Chittenden County. However, this approach
17 might be more valuable in large metropolitan areas where population pressures and
18 traffic delays are much greater. In such cases, we would expect to find delay-related (as
19 opposed to distance-related) accessibility having a greater impact on land use. It is
20 possible that in such cases a land use model integrated with TRANSIMS would yield a
21 more accurate characterization of accessibility, leading to better land use predictions.
22 However, such a model should probably only be run for short-term predictions in highly
23 congested areas, as long-term simulations could result in unrealistic localized stoppages
24 of traffic flow which, in real life, could be addressed through minor interventions, like
25 re-timing signals. Further research is warranted to determine the usefulness of including
26 a micro-simulator in land use modeling for more populous and congested regions and to
27 determine the appropriate time frame of modeling in this context.

28 The integration of TRANSIMS with a land use model may also be valuable in assessing
29 how hypothetical changes to the transportation network might influence the spatial
30 pattern of development, potentially even in smaller metropolitan areas. We are currently
31 in the process of running the 2-way and 3-way models on an alternative scenario
32 involving the construction of a large number of new roads to determine if the 3-way
33 model's land use predictions are more spatially sensitive to the new infrastructure.
34 This and other future research will help us better understand the usefulness and cost
35 effectiveness of complex integrated modeling tools for the planning process.

36

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