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Integrated Land-Use, Transportation and Environmental Modeling: Validation Case Studies

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1 Introduction

For decades the transportation-planning research community has acknowledged the interactions between the evolution of our transportation systems and our land-use, and the need to unify the practices of land-use forecasting and travel-demand modeling (Giuliano 1989; Moore and Thorsnes, 1996; Boarnet and Chalermpong 2001; Cervero 2003). The traditional four-step travel-demand modeling (TDM) process was designed to estimate specific patterns of travel from aggregate spatial and demographic data for a region. Unfortunately, these models are also extensively used to forecast land-use, typically through simple isometric growth of an origin-destination trip matrix. The evolution of land-use patterns, though, is affected by many economic, political, and social phenomena, and extrapolation of past patterns is often insufficient. In addition, there is a two-way interaction between the evolution of land-use and the transportation-network, which is not accounted for in the traditional TDM framework.

Recognizing this interaction, TDMs are linked to land-use models to provide for an integrated land-use/transportation modeling environment. These linkages, and the need to plan for them in an integrated fashion, have been recognized by many researchers as well as by the Federal Highway Administration (USDOT, 1999). 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 required to model the effect of transportation infrastructure development on land-use patterns, and to consider the consistency of transportation plans and programs with provisions of land-use plans in order to receive certain types of federal transportation funds. Other federal programs have attempted to encourage integrated land-use and transportation modeling and planning, including the Travel Model Improvement Program (1992) and the Transportation and Community and System Preservation Pilot program (1999).

The construction of any modeling framework comes at a cost to its owner. Travel-demand and land-use models require, initially,

- Specification/estimation of the model for a base-year,
- Calibration of the model with known base-year data

And, on an ongoing basis,

- Improvement of model function (“training”) with improved coefficients
- Checking of model results frequently for errors in consistency

Most travel-demand or land-use models are never considered factually “complete”, as the update/correction process is ongoing, due to the model complexity and the vast number of inputs, controls, coefficients, and outputs. So the critical factor in the decision to construct a model or augment an existing model is monetary cost or the level of effort required to do so. The relevant question becomes, first, “What will be the value added by this new cost?” and, second, “Does this added value justify the expenditure of effort?”

To answer these questions, we need to understand the concept of "added value". In this context, the value of a modeling platform has two primary components. The first component is the accuracy of its estimations and forecasts, which can be assessed through validation. Some researchers recommend reserving a subset of the calibration data as a "holdout" sample, and using it to validate outputs statistically (Toledo and Koutsopoulos, 2004). However, when counterfactual forecasts (forecasts that represent years in the past) are available, it makes more sense to validate those outputs against real-world data for the forecast year. The second component is the completeness of its outputs, which must consider the policies that will be analyzed by the model. For example, recent federal policy related to vehicle emissions is placing increased output demands on transportation models. Prediction of environmental impacts and network robustness require detailed modeling of traffic flow at the individual vehicle level on a network with full representation of the transportation links. Traditional travel models typically do not provide such level of detail, but newer microsimulation packages can. In this case, a microsimulation package is required to even to get the outputs required.

This project sets out to initiate an analysis of the added validation-accuracy provided by the level of effort required to develop increasingly complex and increasingly disaggregate land-use and travel-demand models. This study examines the forecast output from a range of contemporary model integrations to assess how acuracy has been added relative to the effort required to develop the integrations.

1.1 Background

Many types of interactions between transportation and land-use have been postulated, but most focus on the presence of social/economic/political feedback-mechanisms between the evolution of transportation infrastructure and land use. The search for sustainable transportation strategies hinges on our understanding of the complexity inherent in this land-use/transportation system, and its influence on other economic sectors. Land-use/transportation feedbacks are often manifested in the research community as iterative relationships between land-use forecasting models and travel-demand models. A comprehensive understanding of these feedback mechanisms demands accurate, well-calibrated models for evaluating alternative courses of action, designing sustainable cities and transportation networks, and informing public policy. However, many of the integrated models that have resulted from this need are still in their infancy, and the breadth of feedbacks possible is wide.

The most common feedback mechanism is to guide land-use forecasts with accessibility, which is measured in part by the transportation system. Many contemporary integrated models allow for an iterative-loop between the land-use forecast and travel through the use of an "accessibility" metric (CCMPO, 2008; Voigt et. al., 2009). The implicit assumption in the use of an accessibility metric is that land-use change is guided not only by zoning changes and policy actions, but also by physical accessibilities afforded by the transportation infrastructure. Accessibility is a concept guided by travel cost – a region in the network which is more costly to reach engenders a lower accessibility metric. The best estimation of the travel-cost inputs (typically travel time and other monetary costs) for this accessibility calculation are generated by the travel-demand model. So the feedback mechanism is an iterative land-use forecast at time-step t, which is guided by the land-use at the previous time-step, t-1, and the accessibilities afforded by the transportation network at time-step t.

The fundamental "chicken-and-egg" question regarding the land-use/transportation feedback continues to be unresolved. Is new transportation infrastructure influencing new land use? Or is new land use influencing the placement of new transportation infrastructure? The less common type of feedback mechanism attempts to answer the second question by capturing the influence of land use on the evolution of the transportation-infrastructure network. There are far fewer models that attempt to deal with this feedback relationship, particularly since it cannot be easily codified into an integrated model. However, recent efforts toward this end are encouraging (Aliaga et. al., 2009). The result of a successful integration would be a model which could forecast a new transportation network at time-step t given a transportation network and land-use at time-step t-1. This success may be in conflict with the highly political process which dominates the construction of new transportation infrastructure.

Little research has been done to determine the specific temporal relationships between these feedback mechanisms. The model integrations described previously assume that perfect information about the transportation network is available to developers and planners instantly, and that they begin modifying their plans for land-use immediately. Conversely, it is assumed that perfect information about the land-use is available for transportation-planners, and that they begin to respond with modified transportation-network plans immediately. In fact, neither of these assumptions are true – perfect information is rarely available and the complexities of this process may inhibit planners from acting too reflexively even when good information is available. In addition, even reflexive responses by planners or developers cannot hasten the long lead times involved with the construction of new highway infrastructure.

In this project, we analyze the relationships between several different integrated modeling packages which capitalize on the feedback mechanism between land-use forecasting and transportation-related accessibility metrics. Our focus here is not on the optimal feedback mechanism but on the value-added for increasing resolution (including complexity and disaggregation) in an integrated framework.

Increased resolution can mean different things for travel-demand models and land-use models. As described previously, microsimulation traffic models are capable of modeling traffic flow at the individual vehicle level, but travel model resolution can also be increased by including all of the transportation infrastructure in the travel network (not just major roadway links) and specific characteristics of intersections and modal transfer points. Travel-demand, though, is commonly assessed at the level of a polygon-based traffic analysis zone (TAZ), which aggregates all travel to/from it into a single centroid-node. The resolution of the TAZ may not be compatible with the resolution of the microsimulation traffic network.

Land-use forecasting models often operate in a raster environment, using grid-cell levels as the primary measure of resolution, unless parcel-level data is available. So an increasing level of resolution often corresponds to the ability to input data at a smaller grid-cell level. Integrating a travel-demand model and a land-use forecast means resolving inconsistencies in resolution between the models. Often it is only possible to use the least-resolved model or sub-model.

Twenty different models which each incorporate some level of integration are described by Wegener (2004). Several contemporary models incorporate all three subcomponents. Of these, only MEPLAN and TRANUS are “unified” models (as opposed to “composite” models with separate subsystems with common inputs/outputs). ITLUP (Putnam, 1998), an integrated package consisting of an employment sub-model and a residential-location sub-model, and TRANUS are also noted for their widespread use and applications by MPOs. Recent emissions-related legislation is placing increased output and accuracy demands on transportation models. Accurate prediction of environmental impacts requires detailed modeling of traffic flow at the individual vehicle level. Traditional processes do not provide such level of detail, but newer microsimulation packages can provide this level of detail. None of the integrated models described incorporate activity-based modeling (ABM) or traffic microsimulation in a comprehensive integrated framework.

1.2 Study Area

The study area for this project is Chittenden County, Vermont. The Chittenden County Metropolitan Planning Organization (CCMPO) is centered around a 62-square-mile urban area that contains Burlington, the largest city in Vermont. It is bounded to the west by Lake Champlain and to the east by public lands in the Green Mountains.

The lake and the mountains inhibit travel to the east and the west, creating natural boundaries for the County’s Regional Transportation Model (CCMPO, 2008). Chittenden County has the largest population and employment in the state, with approximately 150,000 residents (of approximately 620,000 in Vermont) and more than 100,000 jobs. Like most regions in the country, the urban core has spread into neighboring municipalities and now includes a suburban development pattern around the outskirts of Burlington.

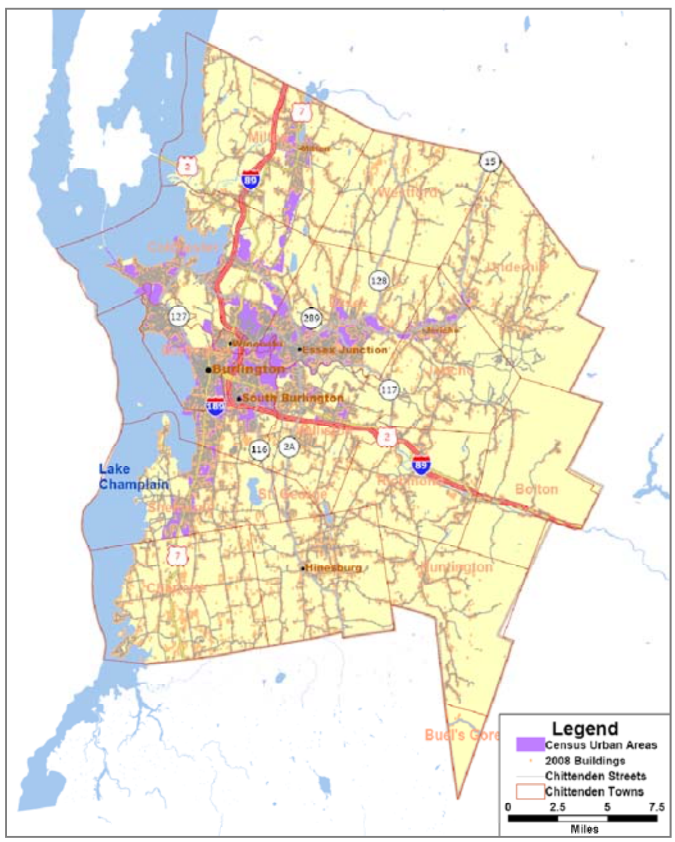

Figure 1 Chittenden County Study Area

1.3 Objectives

While model disaggregation can increase realism, it comes at a cost. Disaggregate modeling is becoming very popular in the research community and the increased specificity of the inputs and the outputs of a disaggregate model is attractive to critics of traditional models. However, the tradeoff between increased accuracy and difficulty of implementation is poorly understood. By no means is the most detailed model always the best. Using a disaggregate approach increases costs in two ways – it increases the amount of data required and it increases the time associated with running the model. Both of these factors combine to have a significant effect on the time and resources necessary to run a model. In addition to the costs associated with building a modeling framework, forecasting models require effort to train and update the model as necessary. Part of this "training" involves forecast-validation and periodic re-calibration to bring the model up to a new base-year. Often the length of time required to build the model means that a base-year update can be made almost immediately after its implementation.

In reality, the correct balance between disaggregation and parsimony 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 Wegener (2004) and Hunt et al (2001), few of these models have been conclusively shown to increase the accuracy of the model output. For instance, data on the year of construction of housing is critical to some land-use models, although it is very expensive to collect. It has not been determined if neighborhood-level measures of housing construction year are sufficient for effective travel-demand forecasts or whether such data need to be collected at the parcel level.

Our interest is to initiate a fundamental evaluation of the benefits of the increased effort that comes with increasing resolution in the modeling of land-use, travel demand, and travel supply (route choice and traffic assignment). The objective is to perform a forecast-validation for forecast-year 2005 on three comprehensive model-integrations, each with a base-year of 1990.

2 Land-Use and Transportation Modeling

We have selected a number of software packages to help us accomplish our objectives. However, we are not using any of the packages for all three sub-components of the integration (land-use, travel-demand, and travel supply), and we are rarely using the full capabilities of each package. Instead, we are evaluating the methodologies and the level of resolution represented by these packages.

Four packages are used in this modeling effort:

- UrbanSim for simulation-based land-use forecasting,
- An MS-Excel-Based process for aggregate land-use forecasting and allocation method (LUAM), a "Lowry-type" model (Rodrigue et. al., 2009)
- TransCAD for estimation of travel-demand and travel-supply,
- TRANSIMS for travel-supply through microsimulation.

A summary of the sub-component functionality of these modeling packages is provided in Table 1.

Table 1 Modeling Packages Used

	Land-Use Forecast	Travel-Demand Estimation	Travel-Supply Estimation
UrbanSim	xx		
TransCAD		X	X
TRANSIMS		(xx)	xx
LUAM	X		

X – aggregate or macroscopic modeling capability
xx – disaggregate or microscopic modeling capability
( ) - available, but not used in this project

2.1 UrbanSim

UrbanSim is a land-use model that simulates urban growth for a region based on externally derived estimates of population and employment growth (control totals). This expected growth is spatially allocated across the landscape to simulate the pattern of future development and land use. While almost all other urban growth models rely on aggregate cross-sectional equilibrium predictive approaches, UrbanSim is an agent-based behavioral simulation model that operates under dynamic disequilibrium in user-defined grid cells, which allows for more realistic modeling of economic behavior. Agents in UrbanSim include both households and employers. UrbanSim operates in an iterative fashion, in which supply-demand imbalances are addressed incrementally in each time period but are never fully satisfied. All of this can be done at any user-specified minimum-mapping unit resolution.

2.2 CCMPO / CCRPC LUAM

The Land Use Allocation Module (LUAM) endorsed by the Chittenden County Regional Planning Commission requires data on the existing numbers of households and employment in each TAZ (CCRPC, 2007). For each forecast year, LUAM allocates to each TAZ the proportion of the forecasted County total households or employment that is equal to the proportion of that TAZ's attractiveness score to the sum of the attractiveness scores for all TAZs in the County. Each TAZ's attractiveness score is calculated on the basis of:

- The estimated average of travel times on the planned transportation network from each TAZ to every other TAZ and the amount of households and employment in each of those TAZs (a TAZ with lower travel times to TAZs with more households and employment has a better attractiveness score)
- The amount of developable land in each TAZ (a TAZ with less developable land has a better attractiveness score)

In making allocations, LUAM constrains its applications of the attractiveness scores in two ways:

- It includes in each TAZ the households and employment corresponding to developments that already have been approved in municipal development review processes (the Permitted Land Use File)
- It limits the total households and employment in each TAZ to totals calculated on the basis of municipal and State development regulations (the allowable land-use (ALU) file).

In summary, LUAM allocates portions of the County's forecasted growth in households and employment to those TAZs that:

1. Are more accessible (relative to all other TAZs) to development in all of the TAZs and
2. Are themselves more developed (relative to all other TAZs)

Until these TAZs are built-out, or reach the maximums set by the ALU file.

A two-stage method is used to account for differing growth rates between urban and non-urban towns in the County to generate TAZ-level forecasts of households and employment, rather than rely totally on the initial LUAM results for all 19 municipalities in the County. The method relies on a distinction between "core" and "non-core" municipalities in the County. The "core" municipalities are those with the highest employment levels in the County (more than 2,500 jobs in 1990). The 11 "non-core" towns are substantially less dense, with smaller populations, and lower employment volumes (less than 1,400 jobs each in 1990).

In the first stage of the endorsed method, the allocations for each of the 11 non-core municipalities are made. Households or employment never exceed the amounts in the Allowable Land Use file. Forecasted households and employment are assigned to the TAZs in the municipality in proportion to the average of two factors - each TAZ's share of the municipality's total Allowable Land Use and each TAZ's share of the municipality's remaining undeveloped development capacity. In the second stage of the endorsed method, the allocations for each of the eight core municipalities are made. LUAM allocations based on TAZ attractiveness (as previously described) of the remaining households or employment in the County after subtracting from the County totals the increased amounts of households or employment allocated to the 11 non-core municipalities from the first stage. So allocations in non-core towns are redistributed by all TAZs in the town when an over-allocation is made, but allocations in the core towns are redistributed throughout all TAZs in the core when an over-allocation is made. So growth in non-core TAZs will not be redistributed to core TAZs.

2.3 TRANSIMS

The TRANSIMS software suite consists of a synthetic population generator, an activity generator, a router, and a microsimulator. The activity generator and the router compute combined route and mode-trip plans to accomplish the desired activities. 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.

While TRANSIMS is designed to allow for using an activity-based approach to transportation demand modeling (using its Population Synthesizer and Activity Generator), the model's Router and Micro-simulator modules can still be applied using standard Origin-Destination (O-D) matrices. This provides for a cost-effective approach for regional planning organizations to take advantage of the increased resolution of the TRANSIMS microsimulator, while depending upon standard O-D matrices at the TAZ level.

2.4 TransCAD

TransCAD makes use of land-use inputs and trip-generation rates to efficiently carry out the sub-models which comprise the 4-step travel-demand and travel-supply modeling process. Trip generation methods are performed to predict productions and attractions or origins and destinations at the TAZ-level. The production process uses cross-classification, regression, and/or discrete-choice methods to turn land-use allocations and published trip generation rates into an estimate of trips produced by a TAZ. The attraction process uses regression to turn land-use allocations into trip-attraction estimates by TAZ. Finally, the productions and attractions are distributed using the Gravity Model and balanced using a singly-constrained or doubly-constrained matrix adjustment to preserve travel within the study region. The resulting origin-destination (O-D) matrix comprises the travel-demand estimate by TAZ. Travel-supply, including mode choice and route choice, can be efficiently modeled in TransCAD. Mode choice is modeled using primarily discrete-choice methods and route choice is modeled with a variety of equilibrium-based behavioral optimizations, including user equilibrium (each user choosing selfishly), system-optimal (each user choosing for the good of all users), and all-or-nothing (each user choosing selfishly, ignoring congestion). The routing step is also known as the traffic assignment, and its results include flow volumes by link, by mode, and by trip purpose.

Land-use packages use current land-use to forecast future land-use. Travel-demand models use land-use to estimate travel-demand, then a travel-supply sub-model to estimate mode choice and routing. Therefore, in order to forecast travel, we first need to use a land-use forecasting tool like UrbanSim or the LUAM, then apply the forecasted land-uses to make an estimate of travel-demand, mode choice, and routing on the road network.

3 Summary of Previous Research

3.1 Previous Model Implementations

The model integrations used in this project benefited from previous implementations of most of the sub-models which focused on calibration for the study area – Chittenden County, Vermont. These implementations were completed under separate grants (Troy and Voigt, 2009; Lawe et. al., 2009) or under Phase I of this project (Troy et. al., 2009).

UrbanSim Implementation for Chittenden County

Much of the work in this project revolved around developing the required data inputs for UrbanSim, of which there is a long list. Some of this data were publicly available and required only minimal processing (e.g. wetlands or floodplain boundaries). Other data sets required many months of effort to conflate, impute, join, quality control, or otherwise process to achieve the required input format. Among these work-intensive data sets were layers giving the year of construction of every structure in the county and assessed land and improvement values for all structures, all of which required extensive data collection and input in city offices. Data on the location and characterization of businesses also required extensive quality control, including manual methods to improve geocoding accuracy and estimate the amount of square footage per worker. Data on zoning had to be integrated from multiple different sources to form a single input with consistent building rules.

One of the key data inputs is a set of “synthetic households” whose characteristics match those of the actual residents in aggregate. Since it is impossible to know the demographic and economic characteristics of households at each individual address, artificial populations must be synthesized by taking actual household counts data from the US Census Public Use Micro Sample (5%), and assigning those to actual locations using a set of fitting algorithms, calibrated with Census joint distribution data. UrbanSim is an agent-based model, and these households then form one of two agent classes, the other being employers.

UrbanSim simulates future urban growth, residential/commercial mobility, and sectoral change based on past trends. To do this, we estimated statistical models, using the database discussed above. These regression and discrete choice models yield coefficients that describe the predictors of land price, residential and commercial moves, and real estate development. These coefficients then serve to drive the model.

Two datasets and versions of the model were built, one for 1990 and one for 2005. Over the course of many months, the 1990 model was perfected until it yielded results that appeared reasonable for years up to the present. The model was run through the year 2030.

Later, the simulated outputs for the year 2005 from the 1990 model were validated against observed data from that year. The 2005 database contained all the same attributes as the 1990 database, but with different values. Validation assesses how the simulated spatial allocation of residential and commercial land uses compares to actual observed data. Predicted and observed indicators for 2005, such as residential units and commercial square footage, were compared at the town level to judge how well the model was calibrated. Overall, our model appeared to predict actual conditions fairly well. After the validation step, the model was then run from the new base year of 2005, out to 2030.

CCMPO Regional Transportation Model in TransCAD

All of the integrated models studied in this project utilize portions of the CCMPO Regional Transportation Model, Version 2.3.0, which is an integration of a LUAM with an enhanced TransCAD-based 4-step TDM based in year 2000 (CCMPO, 2008). The model includes 335 internal traffic analysis zones (TAZs) to simulate traffic flow, and includes an additional 17 external zones to represent traffic entering (or passing through) the County from outside its borders (CCMPO, 2008). The model was calibrated against observed AM and PM peak conditions for its base-year of 2000. The model operates according to the traditional four-step process, including trip generation, trip distribution, mode split and traffic assignment. The LUAM component of the CCMPO Model was re-built in an Excel macro with a base-year of 1990 for this analysis.

TRANSIMS Implementation for Chittenden County

Research documenting the TRANSIMS implementation for Chittenden County was published in 2009 (Lawe et. al., 2009). Implementing only TRANSIMS's Router and Micro-simulator, using O-D matrices, for a given area is typically referred to as a "Track 1" TRANSIMS implementation. In developing the TRANSIMS implementation, every attempt was made to rely primarily on readily available data that would be easily accessible to most metropolitan planning organizations (MPOs). Following model development, several validation experiments were conducted to assess the extent to which the model after calibration replicated observed traffic counts. Preliminary sensitivity analyses were also performed to assess the sensitivity of the model results to changes in the random seed number and to evaluate the impact of changing pre-timed signals to actuated controllers. The study demonstrated that the Track-1 structure and the tools currently available in the model could be used to develop and calibrate a model that works reasonably well with a relatively modest effort for a small to medium-sized MPO. Moreover, for medium-sized areas with little to no congestion, the model does not appear to be sensitive to variations in the seed number, which should increase confidence in the model's results.

The approach taken to build the Chittenden County TRANSIMS network was to start with the TransCAD road network, apply TRANSIMSNet, and then enhance the network integrity manually during calibration. To develop the required trip tables for TRANSIMS, the first step was to extract the following vehicle trip tables from the TransCAD-based travel-demand model, after the mode choice step: (1) Home origin; (2) Work to Home; (3) Non-work to Home; (4) Work to non-home; (5) Non-work to non-home; (6) Medium truck trips; (7) Heavy truck trips; and (8) External to external trips. The extracted PM-peak-hour trip tables were then expanded to the full day using time-of-day distribution factors determined from a household trip diary survey performed in 1998. The results were also checked against NHTS data and permanent vehicle count data. For external-to-external trips, given that the primary external-to-external flow through the region is on Interstate 89, the permanent traffic counters on I-89 were used to generate diurnal patterns for these trips. Finally, the diurnal distribution for non-home-based trips was used to generate daily truck traffic. The calculated PM peak hour to daily adjustment factors are listed in Table 2.

Table 2 Peak-Hour to Daily Adjustment Factors

Trip Type	Description	Adjustment Factor
HBW	Home-based work	4.48
HBO (go to)	Home-based other (leaving home)	13.92
HBO (come home)	Home-based other (returning home)	8.00
NHB	Non-home-based	9.50
Trucks	All truck trips on the network	9.90
Externals	All trips to/from external TAZs	20.00

The study's implementation of the TRANSIMS Router and Microsimulator involved running the following three steps: (1) router stabilization; (2) micro-simulator stabilization; and (3) user equilibrium.

The model was validated against a mid weekday (Tuesday, Wednesday, or Thursday) in September for the year 2000 (the same period and year of calibration as the CCMPO TDM). This was done by comparing the model results to actual field AM and PM counts that covered an extensive portion of the model boundary. The validation exercise focused on the following items: (1) system-wide calibration comparisons to ground counts; (2) use of three directional screen lines throughout the county; (3) diurnal volume distribution for several critical links in the county; (4) limited turn-movement comparisons; and (5) scenario testing.

3.2 Phase I Integrated Modeling Activities

Three composite model-integrations were planned for the integrated-modeling signature project at the TRC for the study area of Chittenden County, Vermont for base-year 1990. A summary of the components of these integrations is provided in Table 3.

Table 3 Model-Integration Components

Integration Code	Land-Use Forecast	Travel-Demand Estimation	Travel-Supply Estimation (Mode Choice and Routing)	Date of Implementation
A	UrbanSim	TransCAD	TransCAD	August 2008

Integration Code	Land-Use Forecast	Travel-Demand Estimation	Travel-Supply Estimation (Mode Choice and Routing)	Date of Implementation
B	UrbanSim	TransCAD	TRANSIMS	January 2010
C	LUAM	TransCAD	TransCAD	March 2010

Integration A

Most of the work on the development of the 1990 base-year UrbanSim model was conducted under a separate USDOT grant (DTFH61-06-H-00022). Details on this process can be found in the Final Report to the funder (Troy and Voigt, 2009). Integration A was completed under Phase I of this project (Troy et. al., 2009). The result of this process was a successful integrated model that could be run from the 1990 base year through 2030, yielding reasonable and internally consistent outputs.

Because accessibility is key determinant of land use, TransCAD is included as a dynamic component in this integration to estimate travel-demand and travel-supply using the UrbanSim land-use outputs. The integration runs the TransCAD component every five years, to update UrbanSim's accessibility values in response to changing land-use patterns predicted by UrbanSim. Hence, land use and transportation interact dynamically in an iterative feedback loop.

The land use and transportation components of this integration make use of nearly identical input data, albeit at different spatial scales, and only limited data conflicts presented themselves as challenges to the model integration process. Unfortunately, the way that the employment types were grouped to form generator classes in TransCAD was different than the way that they were grouped to create employment sectors in UrbanSim. To resolve this issue, the proportion of each generator type was calculated for each UrbanSim employment sector, and the algorithm that handles data transfer between the model systems uses this information to compute trip-generation estimates. Data being passed from the land-use model to the travel-demand model needed to be aggregated to the TAZ scale, while data passed back to the land use model was disaggregated to the grid-cell scale. The end result is that travel accessibilities, based on congested travel times, are computed for each zone pair, and these aggregate-scale accessibilities are then assigned to the individual grid cells within the respective TAZ. Accessibilities are fed back to UrbanSim as the logsum of auto, walk/bike, and transit utilities for each O-D pair.

The integration between UrbanSim and TransCAD was developed using shell scripts, or "wrappers", written in Python, which

- Export land use, number of households, and number of jobs for each trip-generator type from UrbanSim to TransCAD and aggregate to TAZ-level ,
- Run the travel-demand and travel-supply sub-models as scripted in the CCMPO Model (CCMPO, 2008) except that the UrbanSim-generated land-use inputs are substituted for the LUAM sub-model,

- Export accessibilities (based on congested travel-times) at the TAZ-level from TransCAD back to the UrbanSim data cache.

For each forecast-year, land-use, travel-demand, and travel-supply outputs are produced. Research documenting a comparison between Integration A and the stand-alone UrbanSim forecasts for Chittenden County was published in 2009 (Voigt et. al., 2009).

4 Summary of Phase II Integrated Modeling Activities

Phase II of this project includes the development of Integrations B and C, and the forecast-validation of all three model integrations.

4.1 Integrated Model Development

The following parameters were used in the development of these model integrations:

- Travel-supply estimation on the year 2000 road network
- A time-step for land-use forecasting of 5 years
- A population-simulation resolution of 150-meter square grid-cells
- Travel-demand estimation at the CCMPO TAZ-level

Integration B

Just as Integration A benefited from an UrbanSim implementation for the study area funded separately, Integration B benefits from a TRANSIMS implementation for the study area that was funded separately. Integration A served as a foundation for building Integration B, by simply incorporating travel-supply with the TRANSIMS Implementation for Chittenden County.

The Python scripts used in Integration A were modified to facilitate this change. The adjustment factors for the TRANSIMS implementation are run automatically to generate a daily vehicle-trip matrix from the PM-peak-hour travel-demand output which comes out of the TransCAD sub-model. Daily trip-lists were generated for input to the TRANSIMS Router using the PM-peak-hour vehicle-trip data from the CCMPO model (CCMPO, 2008). The vehicle-trip matrix for each trip type are exported as comma-delimited text files and bucket-rounding is applied so row totals are maintained since the number of trips for each origin-destination pair must be integerized for input to TRANSIMS. The script also converts the format from comma-delimited to tab-delimited required by TRANSIMS. The trip lists for each trip type are now ready for input into the ConvertTrips batch which is the first module of the TRANSIMS model.

For Integration A, accessibilities are fed back to UrbanSim as the logsum of auto, walk/bike, and transit utilities for each O-D pair. By incorporating TRANSIMS into the model chain, we now replace the auto utilities in this file with auto utilities based on congested travel times calculated by the TRANSIMS microsimulator instead of the TransCAD assignment module. So the CCMPO model in TransCAD is still used to predict travel-demand (and to predict travel-supply for transit and walk/bike modes) but now the travel-supply step for auto travel is performed in the TRANSIMS implementation. Since the TRANSIMS implementation is a daily model, a new module was added to it that writes out a congested travel time for the 5:00pm to 6:00pm hour calculated by the microsimulator. The new module estimates an average travel time from the average speed on the link during the PM peak hour.

This output matches the PM-peak travel-time output that the UrbanSim accessibilities had been based on.

Integration C

Integration C is actually simply a modified base-year version of the CCMPO Regional Transportation Model (CCMPO, 2008). To standardize the outputs of the CCMPO Model for comparison to Integrations A and B, the LUAM sub-model was re-implemented with a 1990 base-year, and run out to the forecast-year 2005. The LUAM was implemented using the simplified procedure described above (CCRPC, 2007), as a series of Excel-based macros to allocate land-use across the TAZs, guided by "attractiveness scores". High-quality land-use inputs were obtained from the UrbanSim implementation for the LUAM implementation (Troy and Voigt, 2009), and the year-2000 road network was used consistently (as it was in Integrations A and B) to generate the uncongested travel-times used to calculate attractiveness scores by TAZ. The only departure from the documented method was that the permitted land-uses were only available for the later years in this implementation (from 2000 on), so that step where permitted land uses are added to an allocation was not be performed. This omission was not expected to have a significant effect on the results for 2005, since it only involves a check to ensure that permitted land-uses are accounted for in the forecast.

The intent of this integration was to provide a "blind" 15-year forecast with a significantly lower level of effort than the UrbanSim- and TRANSIMS-based integrations. In fact, the total effort for this integration was fewer than 40 person-hours, at least an order of magnitude lower than the levels of effort required for Integrations A or B. The earliest available economic and demographic growth rates dated to 1995 (EPRI, 2000). Since Integrations A and B take advantage of information which became available as late as 1998, the inclusion of growth rates from 1995 were not expected to significantly bias the results of this implementation. Since individual growth rates by town were not available from the 1990s, the regional growth rates provided by EPRI (2000) were used as follows:

- Region 1 (Burlington, South Burlington, and Winooski) was expected to grow 0.4% per year from 1995 to 2005.
- Region 2 (Colchester, Essex, and Williston) was expected to grow 1.9% per year from 1995 to 2005.
- Region 3 (Other towns in Chittenden County) was expected to grow 2.1% per year from 1995 to 2005.
- Employment throughout Chittenden County was expected to grow 2.0% per year from 1995 to 2005.
- Forecasts for total households in Chittenden County were expected to be 65,015 in 2005.

These growth rates were applied linearly for the entire forecast period from 1990 to 2005. It was assumed that all of the towns in a given region grew equally over the 15-year analysis period. Table 4 contains a summary of the town-level data for base-year employment and households, annual growth rates for 1990 to 2005, and subsequent aggregate 2005 estimates.

Table 4 Summary of Town-Level Data for Integration C

Town	Region[1]	1990 Households[2]	1990 Employment[2]	Annual HH Growth Rate[1]	2005 HH Estimate	Annual Employment Growth Rate[1]	2005 Employment Estimate
Bolton	3	526	87	2.1%	718	2.0%	117
Buel's Gore	3	8	-	2.1%	11	2.0%	-
Burlington	1	16,281	32,108	0.4%	17,286	2.0%	43,213
Charlotte	3	1,330	650	2.1%	1,817	2.0%	875
Colchester	2	5,905	4,854	1.9%	7,831	2.0%	6,533
Essex Jct.	2	6,318	6,814	1.9%	8,379	2.0%	9,171
Hinesburg	3	1,476	521	2.1%	2,016	2.0%	701
Huntington	3	616	186	2.1%	841	2.0%	250
Jericho	3	1,487	601	2.1%	2,031	2.0%	809
Milton	3	3,010	1,587	2.1%	4,111	2.0%	2,136
Richmond	3	1,402	357	2.1%	1,915	2.0%	480
Shelburne	3	2,359	2,327	2.1%	3,222	2.0%	3,132
S. Burlington	1	5,411	9,140	0.4%	5,745	2.0%	12,301
St. George	3	285	78	2.1%	389	2.0%	105
Underhill	3	1,013	281	2.1%	1,384	2.0%	378
Westford	3	637	182	2.1%	870	2.0%	245
Williston	2	1,881	15,822	1.9%	2,495	2.0%	21,294
Winooski	1	2,933	1,953	0.4%	3,114	2.0%	2,628
	Totals	52,878	77,548		**64,174**		**104,369**

Sources:
1. EPRI, 2000.
2. Troy and Voigt, 2009.

So the growth of households and employment in each town was calculated for the analysis period to create control totals (shown in bold in Table 4), then this growth was allocated by TAZ according to attractiveness scores. Employment allocation in the non-core towns was performed at the town level – all of the growth shown was allocated within TAZs in the town shown. However, in accordance with the CCMPO/CCRPC LUAM, employment in the core TAZs was performed at the core-level, meaning that all of the growth in the core towns was shared and allocated according to the attractiveness scores of all core-TAZs. This step assumes that employment growth occurs without regard to town boundaries in the core of the study area. Growth was limited according to the "allowable land-use values" for 2005 given in the CCMPO Model and developable land by TAZ, which exempts conserved land (CCMPO, 2008). Although this data would certainly not have been available in 1990, it was used in Integrations A and B. So it was included in this integration to standardize the forecast-validation effort.

Attractiveness scores combined elements of undevelopable land by TAZ (including conserved lands from a 2004 Conserved Public Lands Layer), the ALU for 2005, free-flow travel-times, and the fraction of existing jobs and households by town in each TAZ. Initial household and employment inputs by TAZ were taken from the UrbanSim implementation (Troy and Voigt, 2009). The final 2005 forecast, then, consists simply of these initial inputs by TAZ, added to the growth estimates determined when the town-level growth was allocated by TAZ according to the documented LUAM process. Between 3 and 5 iterative loops by the LUAM were required to allocate all of the forecasted growth such that none of the ALUs were exceeded. The final employment forecast from the LUAM is for total jobs. In order to re-allocate these jobs to the trip-generation classes needed by the travel-demand sub-model, a control file which contains the proportional allocations from 2000 was used. This file also would not have been available for a land-use forecast in 1990, but since it had already been used to re-allocate employment by the other integrations, it was used here to produce an equally-accurate generator-type allocation.

An initial run of the LUAM highlighted a problem with the new inputs (Troy and Voigt, 2009) for the base-year, which made them incompatible with the ALU. An example of this problem is illustrated by the contrast between the initial inputs and the ALUs given in Table 5.

Table 5 Example of the Allowable-Land-Use Problem

TAZ	Town	Households[1]	2005 Allowable Land Use – HHs[2]	Employment[1]	2005 Allowable Land Use – Jobs[2]
29	Burlington	562	510	46	4368
30	Burlington	971	1995	752	976
31	Burlington	0	10	8533	3193
32	Burlington	0	55	6	1022

Sources:
1. Troy and Voigt, 2009.
2. CCMPO, 2008.

These four TAZs correspond to core employment-locations on the University of Vermont campus which are adjacent to one another. When base-year land uses exceed the ALUs, the LUAM re-allocates the excess land uses to other TAZs during the forecast run. The result is a reduction in land use for certain TAZs and a redistribution of the excess into other core TAZs (not the adjacent ones). This reduction is infeasible since existing land uses will not tend to decrease or relocate. In addition, it appears that the ALUs must be in error, since the 1990 land uses seem to exceed to these limits.

This problem likely results from the more detailed investigation of land uses that came from the earlier UrbanSim implementation (Troy and Voigt, 2009) contrasting with the previous aggregate analysis which created the ALUs (CCMPO, 2008). A thorough investigation of the data by TAZ will need to be performed to completely resolve the problem. To work around this problem, the ALUs were adjusted so that they are always equal to or higher than the base-year allocations. ALUs which were already higher than the base-year land use were left as is.

The “integration” step in Integration C consisted simply of substituting the land-use output file (converted to a .csv text file) from the 1990 base-year LUAM for the land-use input file in the base-year 2000 CCMPO Regional Transportation Model (CCMPO, 2008). The CCMPO model can be run for a single-year time-step to develop travel-demand and travel-supply. The single time step was completed for trip generation, trip distribution, mode choice, and assignment, using the year 2000 road network.

4.2 Integrated Model Forecast-Validation

In this project we are forecasting from the year 1990 to the year 2030, so the years 1990 to 2005 are counterfactual and the remaining forecast years are projections. We have a full set of real-world data for 2005 with which to validate the counter-factual forecasts of the year 2005. A similar process was utilized to test alternate transportation-models against the model used by the Sacramento Area Council of Governments (SACOG), SACMET (Hunt et al, 2001). The SACMET study validated alternate runs using the integrated modeling packages MEPLAN and TRANUS.

Data Sources

Sources for 2005 data to be used in this forecast-validation included a housing points layer for 2004 maintained by the CCRPC (VCGI, 2010), the E911 database for Vermont for 2005 (VCGI, 2010), the Covered Employment & Wages from the Vermont Department of Labor (VDOL, 2010), and traffic counts from the CCMPO for 2005 (CCMPO, 2010).

The housing/dwelling units layer for 2004 was developed by the CCRPC from parcel records for Chittenden County. Each housing point in this dataset represents a housing structure in Chittenden County. For each housing structure, attributes indicating the type of structure are included, along with the number of dwelling units (DUs) represented at the point. The dataset is intended to identify the location and type of dwelling units for future land-use and transportation modeling efforts. The number of DUs from this data set in each TAZ was aggregated for the forecast-validation effort.

The E911 database contains site types, locations, and addresses for the nearly 55,000 structures in Chittenden County, as shown in Table 6.

Table 6 Summary of E911 Structures Data

Site Type Code	Site Type Description	No.	Site Type Code	Site Type Description	No.
B1	Bridge	3	**P2**	Health care	60
B4	Campground	1	**P3**	Church	108
C1	Comm. retail/service	2,946	**P4**	Educational	270
C2	Comm. with apt.	35	**P5**	Cultural	64

Site Type Code	Site Type Description	No.	Site Type Code	Site Type Description	No.
C9	Other commercial	242	**P6**	Police Station	10
CF	Commercial farm	106	**P7**	Fire Station	31
CL	Lodging	108	**P8**	Public gathering	110
DV	Development site	257	**P9**	Ambulance house	3
ED	Dry well/hydrant	65	**R1**	Single family res.	36,120
G1	Gated with building	9	**R2**	Multi-family res.	10,160
G2	Gated without bldg.	5	**R3**	Mobile Home	2,549
H1	Hanger	1	**R4**	Other Residential	390
I1	Industrial	168	**R5**	Seasonal single fam.	731
P1	Government/town	221	**R6**	Seasonal home	55

The E911 data was collected originally from 1996 to 1998 as part of the Enhanced 911 Data Development Project. Site coordinates and site information were captured by GPS at each location requiring a new address, or for grandfathered towns that requested GPS work. In addition to the typical sub-meter GPS systems for capture of coordinate data, the data collection system utilized a "dead-reckoning" system that enhanced the GPS data by providing coordinate and heading data during periods of poor GPS reception. Ortho-photography was used for sites not accessible in the field. Data are continually being updated with information including existing features being imported and new features that are created. Since 1999, a bi-monthly update has been produced geographically by the state's E911 maintenance contractor. Locations added or modified after 2005 are not included in the information used for this forecast-validation effort.

The differences between the CCRPC housing ponts layer and the E911 layer is illustrated in Figure 2. The E911 layer for 2008 is shown alongside the CCRPC layer for 2004. The E911 layer focuses on the accuracy of the position of the building, as opposed to the CCRPC layer which simply has an icon for each parcel. All types of buildings are shown in E911 layer, but the CCRPC layer includes only residential parcels. For the forecast validation effort, all of the residential structures (R1 – R6 and C2), and all of the employment-structures (all except R,B, D, and E categories) in the data set were aggregated by TAZ.

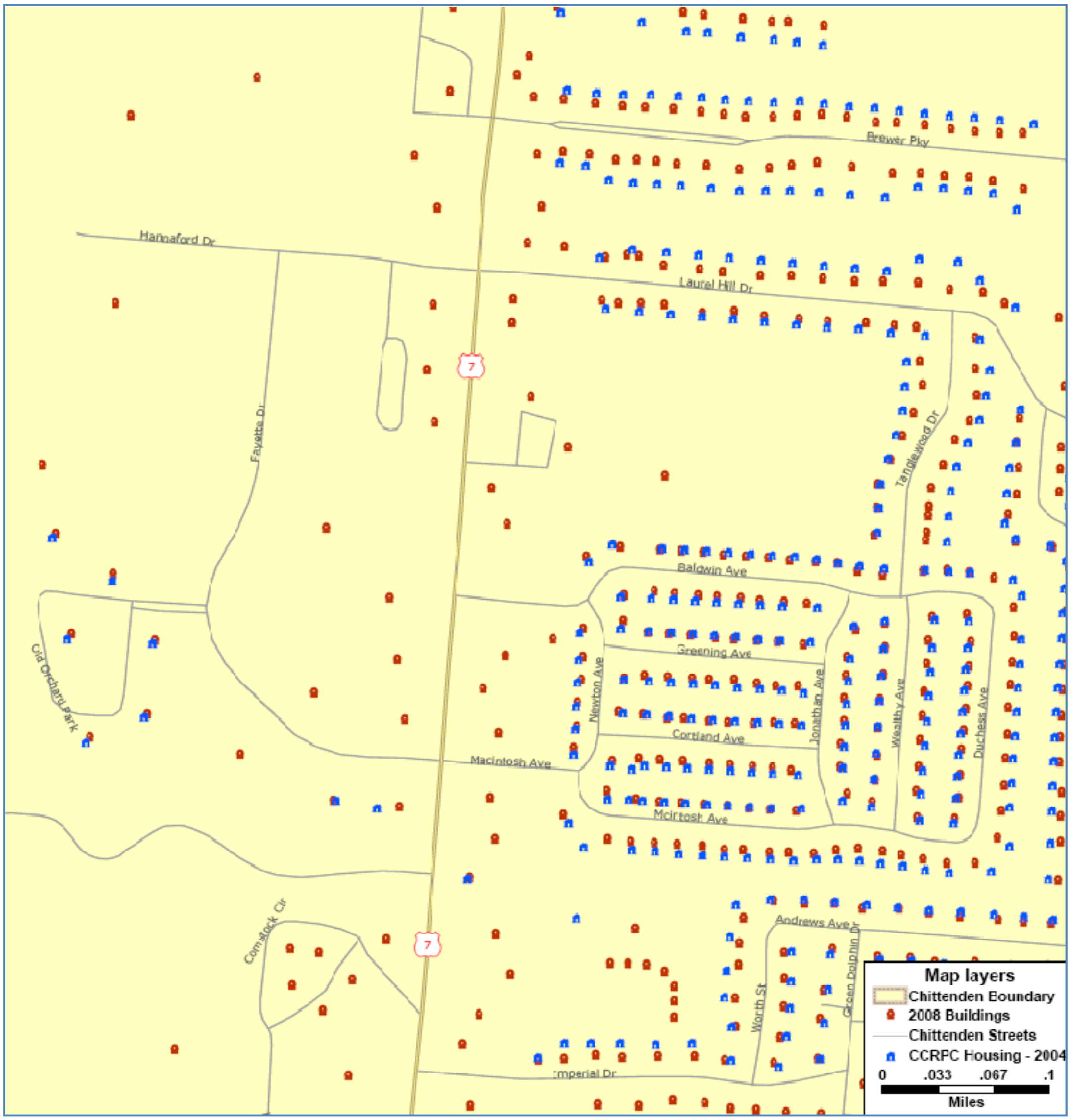

Figure 2 Differences Between the E911 Database and the CCRPC Dwelling Units

The Covered Employment and Wages Data is a product of the Quarterly Census of Employment and Wages (QCEW) program, and is accessible by town at the VDOL website, with annual and quarterly data from 1978 for employment by state, county, and town areas. The QCEW is a cooperative program involving the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor and the State Employment Security Agencies (SESAs). The program produces a comprehensive tabulation of employment and wage information for workers covered by state unemployment insurance laws and federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program. Employment data under the QCEW program represent the number of covered workers who worked during, or received pay for, the pay period including the 12th of the month. For the forecast-validation, total employment by town was collected. Table 7 summarizes for the study area the employment by town from the VDOL for 2005 and the DUs by town for 2004 from the CCRPC information.

Table 7 Summary of CCRPC and VDOL Data by Town for 2005

Town	Status	CCRPC Dwelling Units	VDOL Employment
Bolton	non-core	435	64
Buel's Gore	non-core	9	-
Burlington	core	20,539	32,498
Charlotte	non-core	1,395	485
Colchester	core	7,068	8,438
Essex Jct.	core	7,707	12,414
Hinesburg	non-core	1,658	1,086
Huntington	non-core	783	159
Jericho	non-core	1,826	717
Milton	non-core	3,645	2,476
Richmond	non-core	1,520	1,083
Shelburne	core	2,711	3,272
S. Burlington	core	7,466	17,856
St. George	non-core	284	54
Underhill	non-core	1,189	359
Westford	non-core	792	234
Williston	core	3,322	11,047
Winooski	core	3,086	2,557
	Totals	65,435	94,735

Immediately apparent in Table 7 is the remarkable similarity between the actual households in the study area in 2005 (65,435 DUs) and the number which results from the growth predicted by EPRI (2000) in Table 4 (64,174 DUs in 2005).

The CCMPO maintains a database of traffic counts retrieved and processed from Automatic Traffic Recorder units utilized during annual traffic count programs conducted during non-winter months. Data is available as far back as 1944. This data represents the status of traffic occurrence on any particular segment of roadway or intersection assigned a "Traffic Count Station". Approximately one-third of the links in the CCMPO Model are represented with traffic counts in the PM-peak-hour for 2005. The counts are used for traffic impact studies and scoping study alternatives, where data collected over time can be used to analyze trends. The data is also used to check the accuracy of the CCMPO Model (CCMPO, 2008). All of the PM-peak-hour counts available for 2005 were collected for the forecast-validation effort.

Table 8 provides a summary of the data sources used to validate the model integrations in this study.

Table 8 Summary of Validation Data Sources

Source	Year	Used for Land-Use Validation	Used for Traffic Validation
CCRPC Housing Points	2004	X	
E911 Database for Vermont	2005	X	
VDOL Covered Employment and Wages	2005	X	
CCMPO Traffic Counts	2005		X

Land-Use Results

For all of the integrations, land-use outputs were identical in structure. Since the land-use data had to be sent from the land-use sub-model to the travel sub-model, a convenient text file with the land-use forecast for the year being simulated was readily available for all three integrations. This file contained the forecasted number of households and the forecasted employment by generator-type (low generation, medium-low generation, medium-high generation, high generation, hotel employment and school employment) by TAZ.

Table 9 summarizes the land-use output of the three model integrations by town alongside the base-year totals.

Table 9 Summary of Land-Use Outputs by Town

		2005 Forecasts					
		Integration A		Integration B		Integration C	
Town	Status	HHs	Jobs	HHs	Jobs	HHs	Jobs
Bolton	non-core	684	168	750	704	718	117
Buel's Gore	non-core	20	0	20	0	11	0
Burlington	core	14,683	37,917	14,204	35,633	16,493	32,757
Charlotte	non-core	1,482	819	1,984	4,768	1,817	790
Colchester	core	6,741	7,016	7,172	6,939	7,700	9,579
Essex Jct.	core	7,626	12,651	6,938	9,084	7,578	10,022
Hinesburg	non-core	2,170	955	1,952	1,082	2,016	701
Huntington	non-core	804	254	927	1,762	841	270
Jericho	non-core	1,819	724	2,364	1,216	2,031	819
Milton	non-core	3,838	6,314	4,098	7,632	4,111	2,136
Richmond	non-core	2,691	919	2,392	2,685	1,915	480
Shelburne	core	2,991	5,101	2,549	3,153	4,537	4,866

Town	Status	2005 Forecasts					
		Integration A		Integration B		Integration C	
		HHs	Jobs	HHs	Jobs	HHs	Jobs
S. Burlington	core	5,860	12,717	5,370	9,863	6,320	12,121
St. George	non-core	305	108	322	174	335	78
Underhill	non-core	1,732	377	2,012	1,245	1,384	378
Westford	non-core	886	261	1,509	1,243	870	245
Williston	core	2,505	17,143	2,329	16,136	2,419	17,112
Winooski	core	2,743	2,324	2,688	2,141	3,025	11,814
Totals		59,580	105,768	59,580	105,460	64,121	104,285

Immediately apparent is that the control total for households in Integration C from EPRI (2000) was far more accurate than the sources used for Integrations A and B (Woods & Poole, 2005; Louis Berger, 2006). These other estimates were significantly lower than the EPRI estimate, creating the control-total of 59,580. In addition, it is clear that the three integrations produced significantly different results for both large and small towns.

To validate the three forecasts for households in 2005, cumulative distribution functions (CDFs) were first developed for the sets of TAZ-level household forecasts. Figure 3 shows these CDFs alongside the CDFs for residential structures from the E911 data and for DUs from the CCRPC housing-points data. The y-axis in the CDFs describe the probability that a randomly selected value from the each set of households data will be less than x.

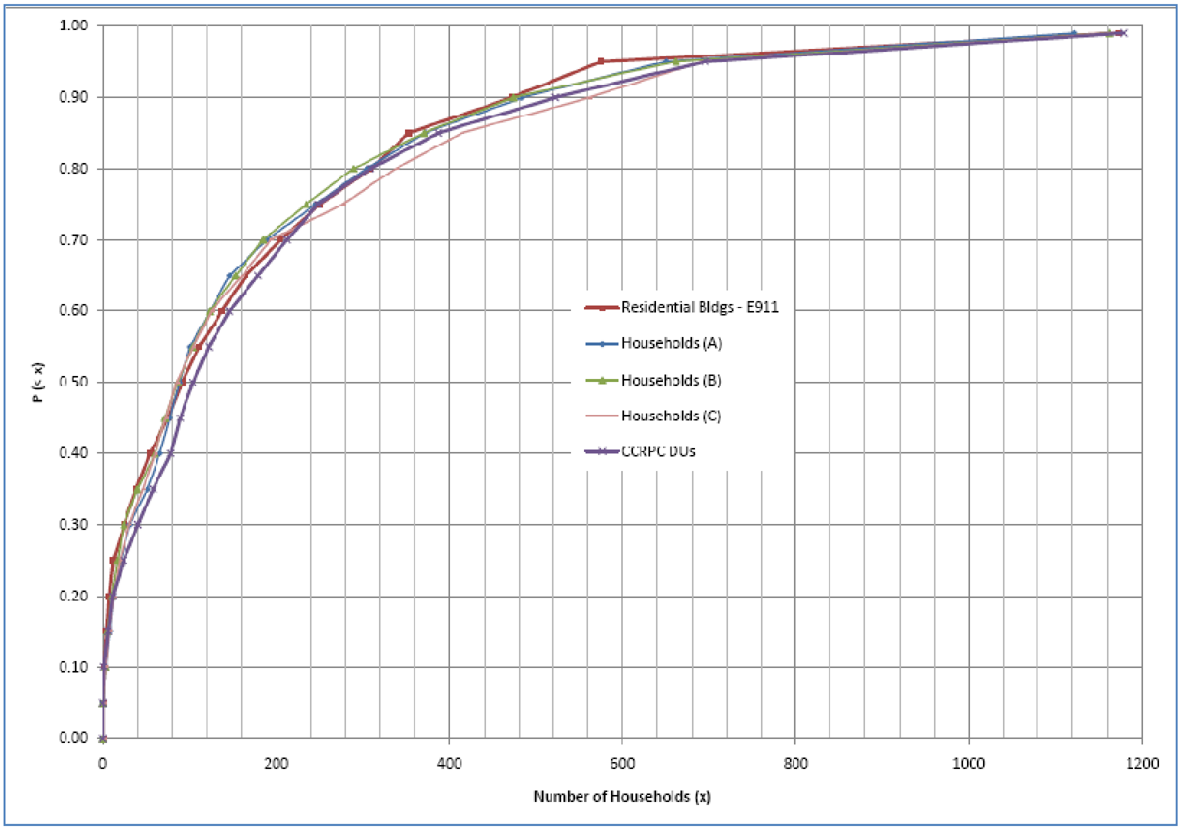

Figure 3 CDFs of the Household Forecasts

In the figure, the CDF for the E911 residential buildings provides a boundary for the other curves, in that at least one household should be present for each residential structure in a TAZ. Therefore, each of the other curves should appear "inside" the concave portion of the "Residential Bldgs – E911" curve. In fact, only the CCRPC DUs curve follows this order correctly. Each of the other curves make “errors” to varying degrees, by moving outside this boundary curve. The CDF curves for Integrations A and B contain significant errors between 100 and 300 households, meaning that these integrations tended to underestimate the number of households in TAZs whose household-size was in this range. Integration C tended to be safer, overestimating the number of households in most TAZs throughout the data set, particularly for TAZs with between 200 and 700 households. However, it is also apparent that the curve for Integration C departed more significantly from the CCRPC DUs curve in this range. This trend implies that Integration C provided a land-use forecast that had fewer underestimations, but may have been less accurate overall than the land-use forecasts for Integrations A and B. Part of the reason for this trend may be the fact that the control total used for Integration C was significantly higher (and more accurate) than the one used for Integrations A and B.

These findings are confirmed by an analysis of the mean-normalized error (MNE) between the households output from the three integrations, the CCRPC DUs, and E911 residential structures data (for those TAZs where an under-prediction was made). Table 10 provides a summary of the MNE resulting from the comparison of the E911 residential structures data and the output of the three integrations.

Table 10 Mean Normalized Errors for Household Under-Prediction Error

Comparing the E911 Residential Structures to:	Number of TAZs in Error		Mean Normalized Errors: All Towns	Urban Towns	Non-Urban Towns
Integration A	137	40.9%	-37.7%	-41.2%	-12.8%
Integration B	138	41.2%	-43.0%	-44.8%	-19.3%
Integration C	132	39.4%	-41.1%	-46.6%	-14.7%

As expected, although fewer TAZs are in error for Integration C, the magnitude of the error is fairly high for Integration C, especially in the urban towns in the study region. To get an estimate of the overall accuracy of the household-forecasts for all three integrations, the MNE and the root-mean-square normalized-error (RMSNE) of each forecast relative to the CCRPC DUs was determined. A summary of these results is provided in Table 11.

Table 11 MNE and RMSNE Comparing CCRPC DUs to Household Forecasts

Comparing the CCRPC 2004 DUs to:	MNE			RMSNE			MNE, Weighted by TAZ
	All Towns	Urban Towns	Non-Urban Towns	All Towns	Urban Towns	Non-Urban Towns	All Towns
Integration A	15.5%	12.4%	34.2%	130%	138%	63%	-0.03%
Integration B	5.6%	-1.6%	48.7%	97%	100%	74%	-0.03%
Integration C	27.7%	29.3%	17.9%	181%	195%	37%	-0.01%

The MNE results indicate that routine over-predictions of household growth more than cancelled out the under-predictions shown in Table 9, resulting in positive (over-predictive) overall MNE for all integrations. Integration B, which utilizes the increased precision of TRANSIMS in predicting travel times, was found to be the most accurate household-forecast in the urban towns. In the non-urban towns, both integrations which relied on a travel-time based accessibility score were found to be less accurate than Integration C, which ignored travel times and enforced stricter town boundaries when forecasting growth. This finding suggests that the contributions of a package like TRANSIMS, which increases the precision of traffic estimation, are more significant in urbanized areas, but are not as useful in non-urban towns, where travel time may have little influence on residential growth. It is also possible that travel-time continues to influence residential growth in non-urban areas, but the ability of our travel models to accurately predict travel-time in non-urban areas is compromised. These findings are more pronounced when the RMSNE is considered. The RMSNE eliminates the cancelling effects of positive (over-predictive) and negative (under-predictive) errors, assessing simply the magnitude of all errors, and reveals more about the quality of the Integration B forecast. The RMSNE for the urban towns indicates that the relatively low MNE found for Integration B for the urban towns was masking a significant “cancelling” effect from relatively large negative and positive errors, which is revealed when the RMSNE is considered.

The weighted MNE confirms that the control totals for households for 2005 were quite accurate, leaving the allocations as the primary source of error for these forecasts.

To examine the three forecasts for employment in 2005, PDFs were first developed for these employment forecasts. Figure 4 shows these PDFs alongside the PDFs for non-residential structures from the E911 data.

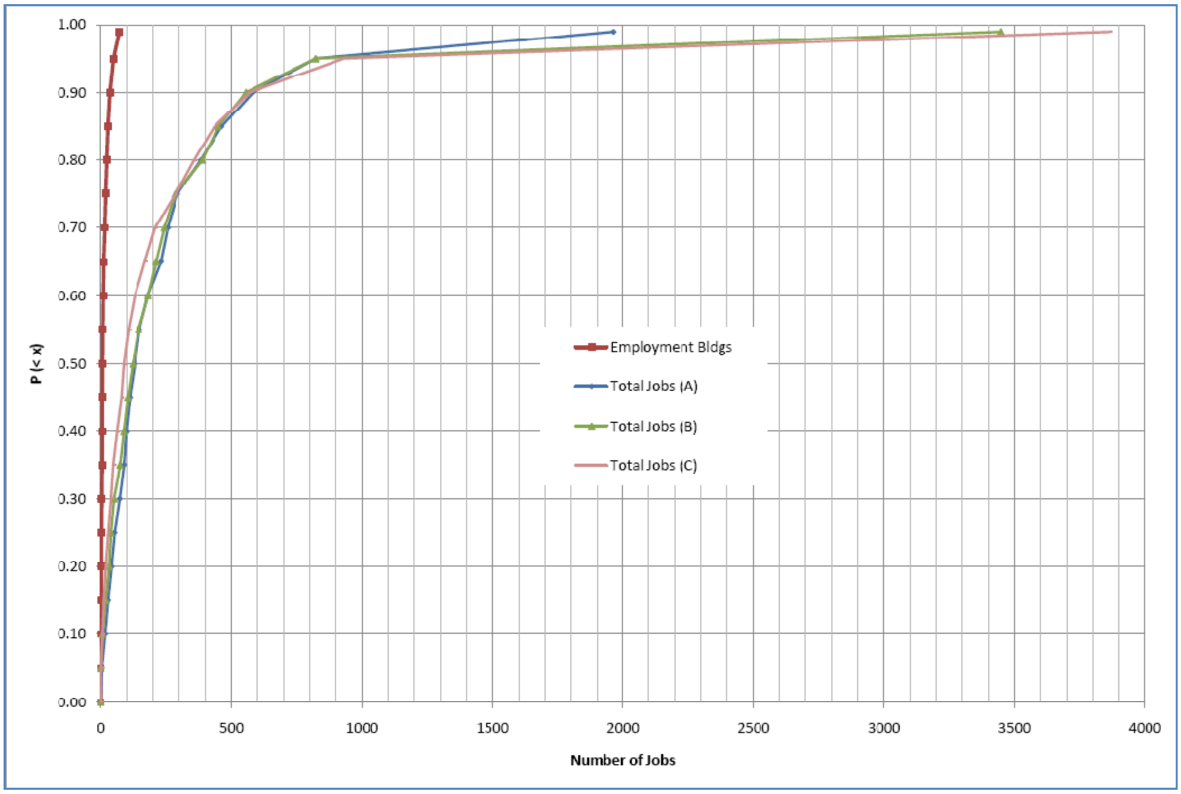

Figure 4 CDFs of the Employment Forecasts

This figure confirms the significant differences between the UrbanSim land-use allocation (Integrations A and B) and the LUAM (Integration C) for TAZs with between 0 and 300 jobs. However, it surprisingly also indicates that the TRANSIMS component of Integration B skews the land-use allocation to be a bit closer to the LUAM-based forecast at high-employment TAZs (larger than about 1,200 jobs). In the figure, the CDF for the "Employment Bldgs" from the E911 data provides a boundary for the other curves, in that at least one job should be present for each non-residential structure in a TAZ. Therefore, each of the other curves should appear entirely to the right of this curve. Most of the integrations appear to avoid this type of under-predictive error. However, a more detailed analysis of the data reveals otherwise, as shown in Table 12.

Table 12 Fraction of TAZs with an Under-Prediction of Employment Levels

	Number of TAZs in Error					
Comparing the E911 Job-Locations to:	Total Other		School (79 TAZs)		Hotel/Motel (39 TAZs)	
Integration A	18	5.4%	28	35.4%	14	35.9%

Comparing the E911 Job-Locations to:	Number of TAZs in Error: Total Other		School (79 TAZs)		Hotel/Motel (39 TAZs)	
Integration B	31	9.3%	28	35.4%	16	41.0%
Integration C	31	9.3%	35	44.3%	12	30.8%

Under-predictive errors were fairly frequent at TAZs with relatively low employment levels. Table 12 also shows a similar comparison between E911 buildings which are used for lodging (CL) and educational purposes (P4) and forecasts for hotel/motel and school employment. Errors of this type were made at approximately 1/3 of the TAZs which included either educational or lodging structures at similar levels between the three integrations.

To get an estimate of the overall accuracy of the employment forecasts for all three integrations, the MNE and the RMSNE of each forecasts relative to the VDOL data (by town) was determined. A summary of these results is provided in Table 13.

Table 13 MNE and RMSNE Comparing VDOL Employment to Employment Forecasts

Comparing the VDOL Job Totals to:	All Towns	Urban Towns	Non-Urban Towns	All Towns	Urban Towns	Non-Urban Towns	All Towns
	Mean Normalized Error			RMSNE			MNE, Weighted by Town
Integration A	34%	11%	48%	65%	33%	79%	0.6%
Integration B	231%	-8%	371%	420%	28%	517%	0.6%
Integration C	34%	61%	18%	94%	140%	52%	0.6%

Integration B now seems to perform the most poorly of the three, due to significant overestimation of employment totals in non-urban towns. However, Integration B still performs best in urban towns, although its benefits are reduced when the RMSNE is considered. Integration C continues to perform best in non-urban towns, which is consistent with the findings of the household-forecast validation. Integrations A and C seem to forecast employment better than households whereas Integration B did a better job with the household forecast. This finding suggests that the differences between urban and non-urban growth are more pronounced for employment forecasts – travel-time predictions seem to play a greater role in employment forecasts.

Traffic Results

The validation of the travel-supply estimations for the three model integrations focused on predicted traffic volumes by link on the network. Traffic output was available by road-network link for all integrations. Integrations A and C used an identical road network from the CCMPO Model to model travel-supply, but the TRANSIMS network was developed separately during the TRANSIMS implementation project (Lawe et. al., 2009). During the forecast-validation, it was determined that the directional topology of the TransCAD network and the TRANSIMS network were not consistent so a directional comparison of traffic volumes was not possible. However, the TRANSIMS links and the TransCAD links were perfectly co-aligned so that total volumes could be compared for all of the links with traffic counts available. Table 14 provides the RMSNEs by town (urban/non-urban) and by road classification between the PM-peak-hour traffic counts for 2005 and the estimate traffic volumes from each of the three integrations.

Table 14 RMSNEs Comparing PM-Peak Traffic Counts to Estimated Volumes

Comparing PM-Peak Traffic Counts to Forecasted Volumes for:	All	In Urban Towns	In Non-Urban Towns	Interstates	Urban Limited Access Highways	Urban Principal Arterial	Minor Arterial	Major Collector[1]	Local
Integration A	94%	88%	115%	37%	34%	68%	63%	128%	96%
Integration B	321%	73%	743%	24%	21%	44%	55%	513%	282%
Integration C	56%	44%	93%	11%	12%	42%	35%	75%	75%

Notes:
1. Rural and non-rural major collectors were combined, since these distinctions were not found to coincide with the CCMPO urban/non-urban distinctions.
2. All values are RMSNE.

TRANSIMS travel-supply data is simulation-based, so each run includes some degree of stochasticity. Unfortunately, it was not feasible to perform multiple runs of Integration B for this project, so the results from a single run had to be used in the forecast-validation. For the travel-supply estimations, Integration C performed significantly better than the UrbanSim-based integrations when the RMSNE was considered. TRANSIMS again seemed to markedly improve the fidelity of the estimation in the urban core, but its estimations were compromised significantly in the rural towns. Much of the error in the travel-supply estimations for Integrations A and B result from their inaccuracy on major collectors and local roads.

One of the characteristics of Integration C that may have improved its travel-supply estimation is its ability to remain accurate in the non-urban portions of the study region. It is possible that accurate estimation of land use in non-urban areas may lead to improved traffic estimation overall. Another possibility is that the capability of Integration C to maintain a constant level of resolution (the TAZ-level) throughout the integrated modeling process improves its overall fidelity. For these integrations, travel-supply is being modeled on an aggregated road network, which eliminates many local streets and replaces them with idealized “centroid connectors”. When this type of network is being used (as it is for many existing TDMs), the most efficient approach may be to utilize lower-resolution land-use inputs for the forecast.

Another way of examining the reasons for the performance of one integration over another is to examine the differences in the output of the three models integrations. Figure 5 provides a comparison of the CDFs of the speed-output of each model. These speeds are associated with each of the links in the road network, so there are nearly 1,700 data points for each integration.

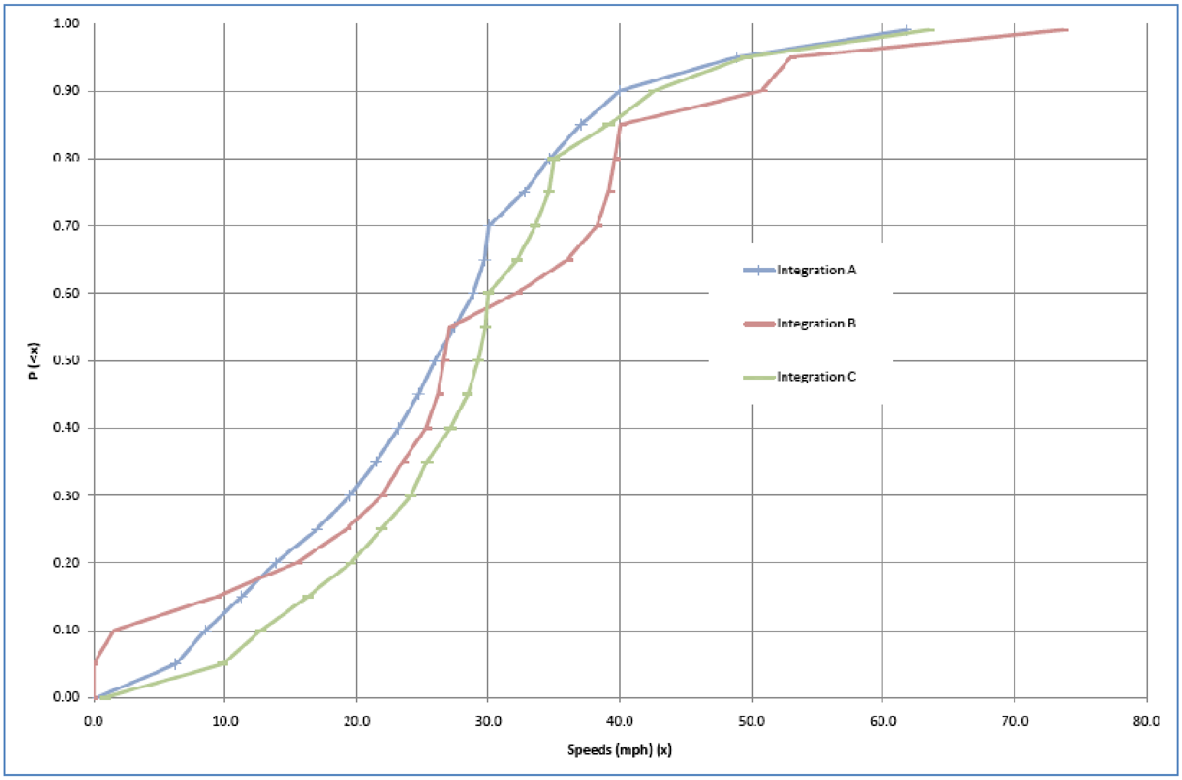

Figure 5 CDFs of Traffic-Speed Estimations

The significant differences in the way that travel-supply was modeled by each of the integrations is evident in the figure. Integration A seems to provide a more continuous distribution of speeds than either Integration B or Integration C. Integration C clusters more speeds around 30 and 35 mph, common speed limits in the urban core, whereas Integration B exhibits a similar clustering, but around 27 and 40 mph, respectively. The reasons for these differences are not clear. These speed variations may provide an explanation for some of the land-use allocation differences between Integrations A and B, since travel-times between TAZs contribute significantly to the attractiveness of a TAZ for future development, and these integrations used a parallel UrbanSim process for land-use forecasting.

TRANSIMS' simulative process in Integration B allows more low speeds since travel is being modeled down to the vehicle-level, and starts/stops are included, and more high speeds, in excess of the speed limits. The global maximum speed in TRANSIMS is about 84 mph, and the vehicle speed is dependent on this global maximum, the speed limit on the link, the maximum attainable speed of the vehicle, and the gap between the vehicle and the one immediately ahead in the same lane (Williams et. al., 1997). These simulative results create more accurate estimates of travel and forecasts of land use in areas of traffic congestion, but appear to break down significantly on non-congested streets. There could be a number of reasons for this result, including the possibility that the rules governing vehicle-speeds in TRANSIMS are more accurate for congested travel, but that drivers behave differently in less congested, non-urban conditions. Other studies suggest that TRANSIMS may have the tendency to routinely over-estimate travel speeds (Rilett et. al., 2000; Rilett, 2001).

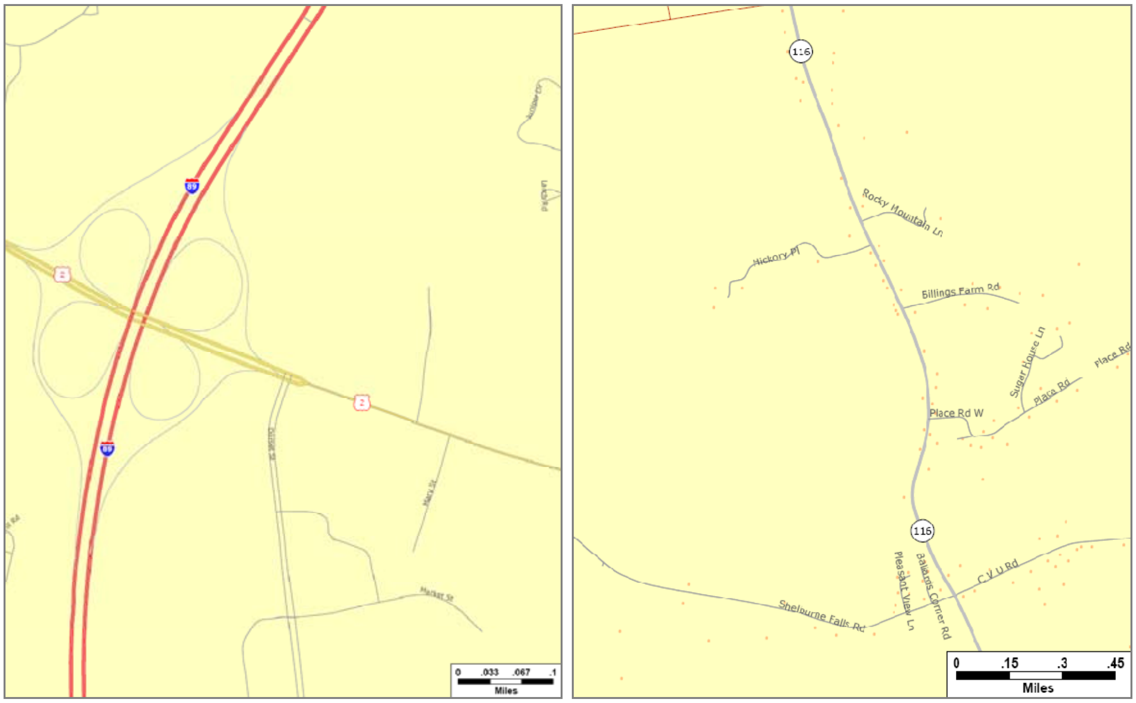

Figure 6 Route 116 in Hinesburg and Willison Road (Route 2) in South Burlington

This situation is further illustrated by the results for specific links in the network. Figure 6 contains detailed views of two different links in the CCMPO network – a rural minor arterial, Route 116, in Hinesburg, and an urban principal arterial, Williston Road, in South Burlington. Williston Road at this location is one of the most congested links in the PM-peak hour in the County.

Table 15 provides the outputs of the travel-supply sub-model for each of the links in Figure 6 and another link, Heineberg Dr. which also experiences moderate congestion at the PM-peak hour. Table 15 should be viewed with caution, since the directional results for the Integrations may not be consistent with one another, or with the PM-peak traffic counts shown. Only total link volumes were compared in this study, and speeds were evaluated as distributions, so directions are not used in the comparison.

Table 15 Specific-Link Speed Comparison

Road Name	Route 116	Route 2 (Williston Road)	Heineberg Dr.
Length (mi.)	2.09	0.01	0.51
Class	Minor Arterial	Urban Principal Arterial	Urban Limited Access
Capacity (vph)	700	1600	1000
Speed (mph)	50	35	50
Status	non-core	core	core
No. of Lanes Each Way	1	2	1
Volume Delay Alpha	0.25	0.25	0.25
Volume Delay Beta	4	4	4

	Road Name	Route 116	Route 2 (Williston Road)	Heineberg Dr.
	Walk Time (min.)	41.78	0.18	10.13
	Free-Flow Travel Time (min.)	2.51	0.02	0.61
PM-Peak Traffic Counts	**AB_Count**	675	1865	718
	BA_Count	333	1778	966
Integration A	**AB_Volume**	914	2217	1089
	BA_Volume	330	3269	1029
	AB_V/C	1.3	1.3	1.1
	BA_V/C	0.4	2.0	1.0
	AB_Speed	23.4	0.3	21.0
	BA_Speed	49.4	6.7	37.3
Integration B	**AB_Volume**	815	1154	698
	BA_Volume	614	2039	1026
	AB_V/C	1.2	0.72	0.70
	BA_V/C	0.9	1.27	1.03
	AB_Speed	46.3	5.4	34.4
	BA_Speed	53.0	23.7	51.2
Integration C	**AB_Volume**	845	1745	681
	BA_Volume	418	2238	924
	AB_V/C	1.2	1.0	0.7
	BA_V/C	0.6	1.3	0.9
	AB_Speed	27.8	0.9	33.7
	BA_Speed	48.1	18.9	41.6

The improved performance of the TRANSIMS integration (Integration B) with respect to traffic volumes and PM-peak traffic counts is evident when the more congested links (Williston Road) is considered. The most dramatic difference between Integration B and Integrations A and C, however, is in the speeds estimated on each link. TRANSIMS allows for higher speeds on all links. In fact, the average speed of Integration B for these three links is 35.7 mph, whereas the average speeds for the Integrations A and C for these three links are 23.0 and 28.5, respectively.

An initial analysis of the speed data revealed that one of the links in the CCMPO road network was coded with a 140-mph speed limit, so the models were allowing speeds on this link up to 140 mph. This value turned out to have been a coding error made when the road network for the CCMPO model was originally developed and was corrected. The link in question should have been coded with a 40-mph speed limit. All of the data analyzed in this forecast-validation excludes that link, and two others whose output may have been significantly affected by the error. Since the link in question was near the edge of the network, it was not expected to significantly affect the other results.

5 Conclusions

The primary conclusions of this research relate to the need to balance conflicting objectives when deciding what level of integrated modeling is appropriate. These conflicting objectives include:

- Level of Effort and Value
- Urban Areas and Small / Medium MPOs
- Disaggregate Data and Cost

5.1 Level of Effort and Value

Using the results of the forecast-validation as an indicator of the accuracy of the model integrations, it is clear that there is a balance between the level-of-effort put into the development of a model, and the accuracy added by that effort. Integrations A and B were significantly more costly to implement. UrbanSim improves the ability of the integrated models to forecast land-use, and TRANSIMS improves the ability of the integrated models to estimate travel, but it is not clear yet that these improvements justify the added effort.

Admittedly, this conclusion is based on the assessment for a particular study region, in a particular temporal state, and cannot be extrapolated to similar implementations for other MPOs and different forecast-durations. The CCMPO study region has been a relatively slow-growing MPO between 1990 and 2005, and is being assessed only 15 years into a 40-year forecast. It is possible that the more advanced integrated models (A and B) gain value faster as the forecast-year gets farther from the base-year, when significant growth has been experienced, or for a region where faster growth is experienced.

It may also be true that continued refinement of the more advanced model integrations (A and B) will lead to exponential performance improvements which will create improved accuracy. However, for small or medium-sized MPOs with limited resources, the costs associated with these refinements need to be evaluated carefully.

5.2 Urban Areas and Small / Medium MPOs

Local elected officials in urbanized areas with populations above 50,000 have a federally-mandated and clearly defined role in shaping their region's transportation vision and priorities through MPOs. In urbanized areas above 200,000 people like Chittenden County, MPOs are designated as Transportation Management Areas (TMAs) and have significantly greater planning and investment decision-making authority. About 52% of the 381 MPOs in the United States represent populations of fewer than 200,000 people, 36% represent populations of 200,000 to 999,999 people, and 11% represent populations of 1 million or more people (GAO, 2009).

The CCMPO, as a medium-sized MPO, contains within its boundaries a significant portion of non-urban and rural TAZs. The 8 towns represented as “core” towns in the CCMPO region comprise only 36% of the total area of the County. Only 10% of the area of the County is represented by the “Urbanized Area” distinction according to the U.S. Census (USCB, 2000). Therefore, accurate forecasting in rural regions is critical for the CCMPO, and is likely to be critical for other medium and small MPOs. Forecasting methods which are equally accurate in urban and non-urban areas will continue to be important for transportation planning in these MPOs.

This research suggests that the accuracy of advanced integrated models may be limited to areas where travel congestion affects travel time. Simpler forecasting and estimation methods may still provide better accuracy in areas where congestion does not significantly affect travel time. In addition, the inaccuracy of travel estimation in non-urban areas may make the inclusion of travel-times in accessibility and attractiveness metrics in a model-integration less effective.

5.3 Disaggregate Data and Model Error

The collection of disaggregate data for more advanced modeling purposes increases the level of effort in two ways – by increasing the collection effort, and by increasing the model-development effort. Increasing the resolution of input data creates the possibility for additional errors in consistency between model components, and increases the potential for simpler input-errors. So the decision to collect increasingly disaggregate data must be made carefully, with consideration of the value that will be added by the additional model-resolution provided and consideration of the decisions to be supported by the model. .

Even with the substantial efforts involved in the development of the Chittenden County implementations described in Section 3, inconsistencies and errors were discovered which skewed the accuracy of the 2005 forecast (refer to Section 4 for details). It is likely that these inconsistencies will have further skewed the 2030 forecast. The potential for these types of inconsistencies to be present increases with increasing resolution of both the land-use and travel model components. Whereas errors in aggregate models are likely due to aggregation processes, errors in disaggregate models are more likely due to inconsistencies or errors in the model specifications. Although it is reasonable to expect that the errors in a disaggregate model can be resolved, that resolution is costly and costs have to be considered in the implementation of any land-use or transportation planning model.

6 Future Directions

The forecast-validation performed for this analysis provides insightful information about the accuracy of the three model integrations being studied. However, a number of critical questions about the findings of this study can still be answered with the following additional runs of the integrations:

1. All integrations can be run using a more detailed streets network and/or smaller TAZs in order to determine the effect of spatial resolution of the road network on model outputs and effectiveness.

2. All integrations can be run using a 15-year time-step (like Integration C) instead of a five-year time-step in order to assess the effect of land-use model temporal resolution on model outputs and effectiveness.

3. All integrations can be repeated using a TAZ-level spatial resolution for the land-use simulations (like Integration C) in order to assess the effect of spatial resolution of the land-use simulation on model outputs and effectiveness.

4. All integrations can be run using a daily travel-demand and travel-supply model (like Integration B) to determine the effect of a standardized travel-model temporal resolution on model outputs and effectiveness.

Once the outputs of each of these composite integrations have been validated in accordance with the process outlined in this report, a decision can be made about the value of additional effort to improve each of the integrated models. Model integrations that are determined to be useful to future research efforts can be re-calibrated, to take advantage of the 2005 data used in the forecast-validation. The goal is to improve the fitness of any integrated models carried forward in Signature Project 1B.

Future research is also need to evaluate the suitability of these advanced model integrations for various policy applications. Newer policies related to the evaluation of the impacts of transportation and land-use on the environment will likely require new data from land-use and travel models. In many cases, there may onlybe a few types of models capable of producing the new data. Therefore, a comprehensive comparison of the outputs of these model integrations against the data required for various policy evaluations is needed to complete this investigation.

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