
Lightning Talks
Innovations in Travel Modeling 2014

[1]

The light in lightning

Rick Donnelly
Parsons Brinckerhoff

The **essence** of…

- Works in progress
- My next big thing
- Questions
- Rants
- Product announcements
- Upcoming RFPs
- Help or ideas wanted
- Research topics
- Challenges
- …

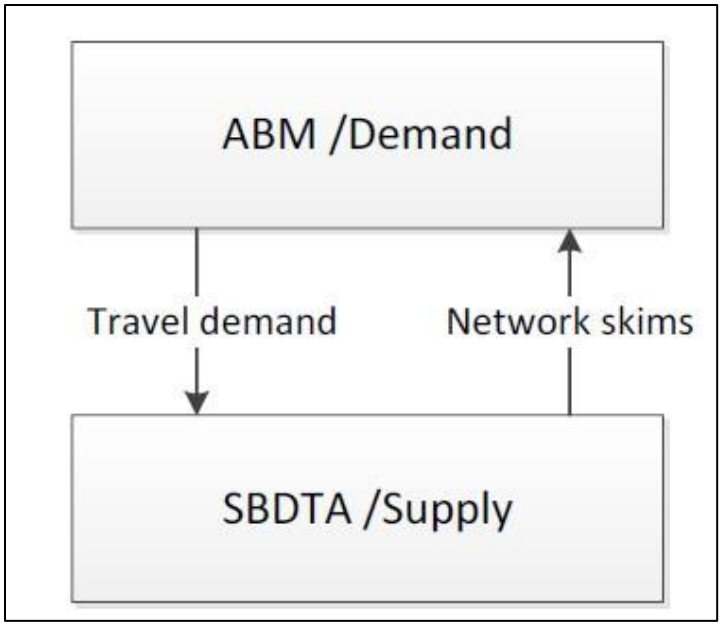
5 minutes
5 slides
No questions
No exceptions

[2]

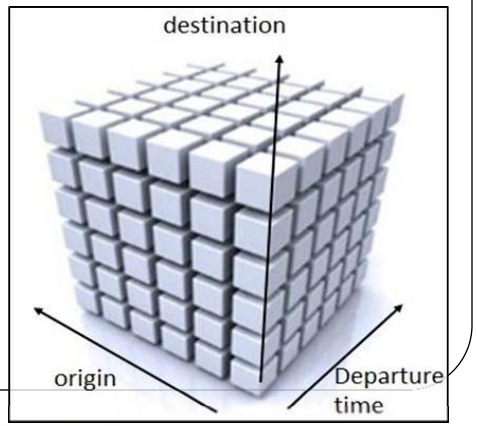
A computationally efficient approach to retaining zone-pair travel time in DTA for ABM

Yi-Chang Chiu
University of Arizona

Introduction



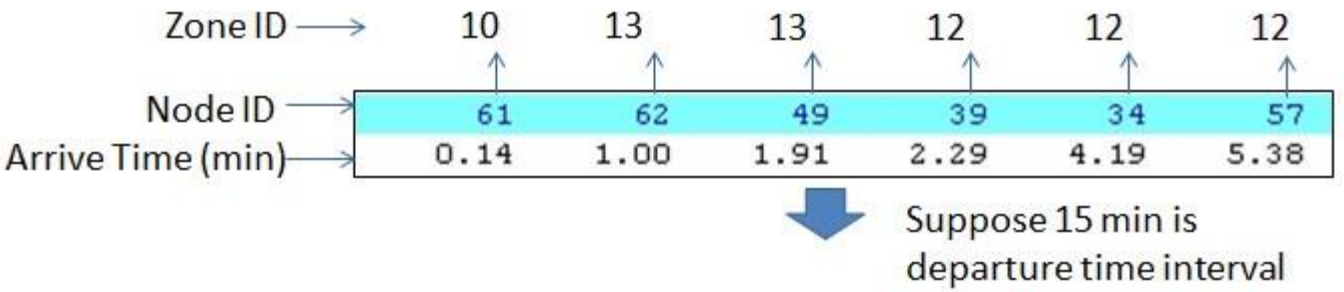
- **Massive Size of Skim matrices**
  - Example: 4,000 TAZs, 15 min skim interval, 24 hrs = 1.5B cells.
- **Pre-computed and stored and read into memory.**
- **Could we do without skim matrices?**



Trajectory Mining

THE UNIVERSITY OF ARIZONA

- **Vehicle Trajectory - Direct output of DynusT**
  - Step 1: Scan and retrieve $\binom{n}{2}$ time stamps from each vehicle trajectory.
  - Step 2: Record and average travel time values for corresponding ODT.

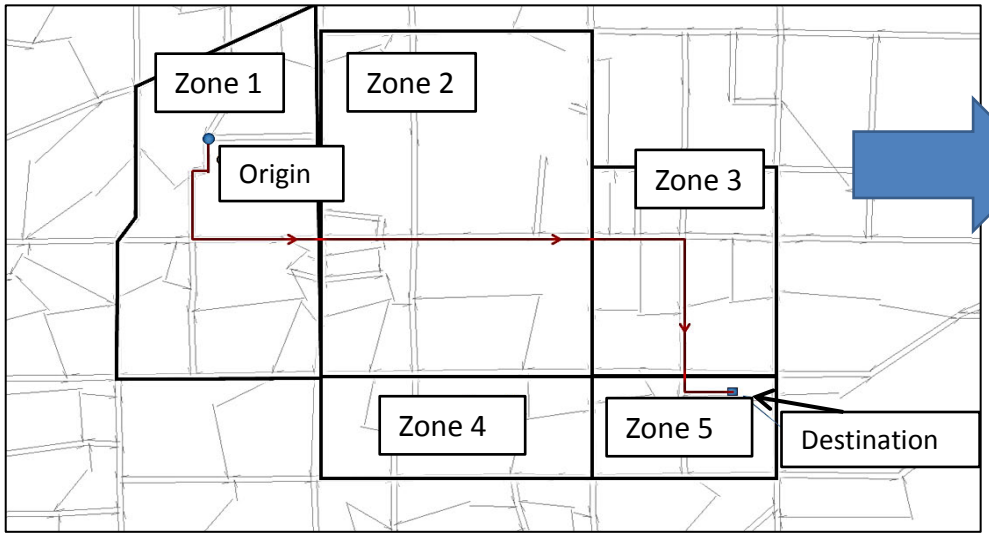


ODT	Travel time entities
(10,13,1)	0.86, 1.77
(10,12,1)	2.15, 4.05, 5.24
(13,12,1)	1.29, 3.19, 4.38, 0.38, 2.28, 3.47

ODT	Travel time results
(10,13,1)	1.315
(10,12,1)	3.81
(13,12,1)	2.50

Trajectory Mining

- **Trajectory mining (with correlation)**
  - Decompose trajectories into the times-space diagram.
  - Do BFS when trying in the compressed diagram.
  - Compressed structure → less memory usage.
  - Use existing trajectory info & do BFS instead of TDSP → less CPU time.



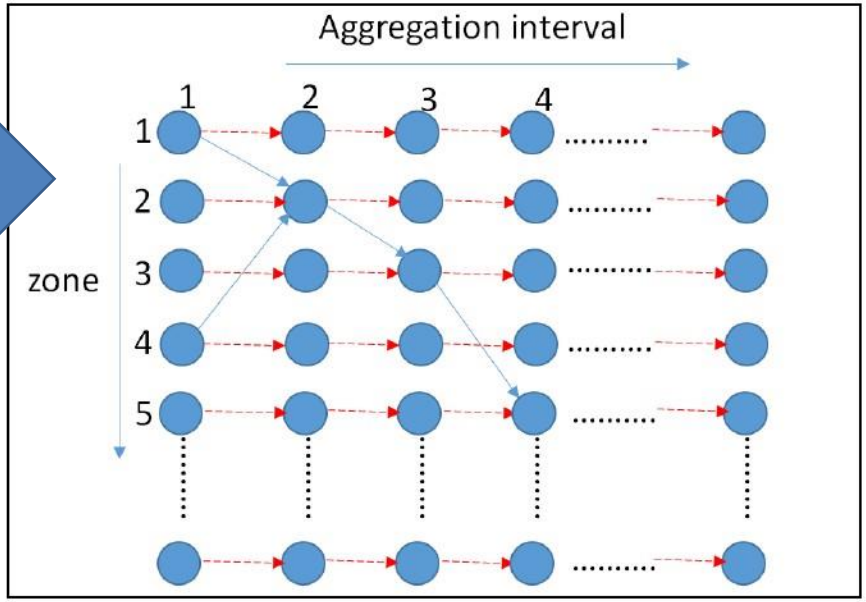


Figure 4: Compact time-space diagram

Results Highlights

- For a given ODT query
  - *If (ODT) is found in the ST tree*
    - Return travel time
  - *Else*
    - Call TDSP for this ODT
- **Compared to matrices**
  - 12.8% memory usage
  - 91% odt travel time can be captured by vehicle trajectories.
  - Comparable run time.

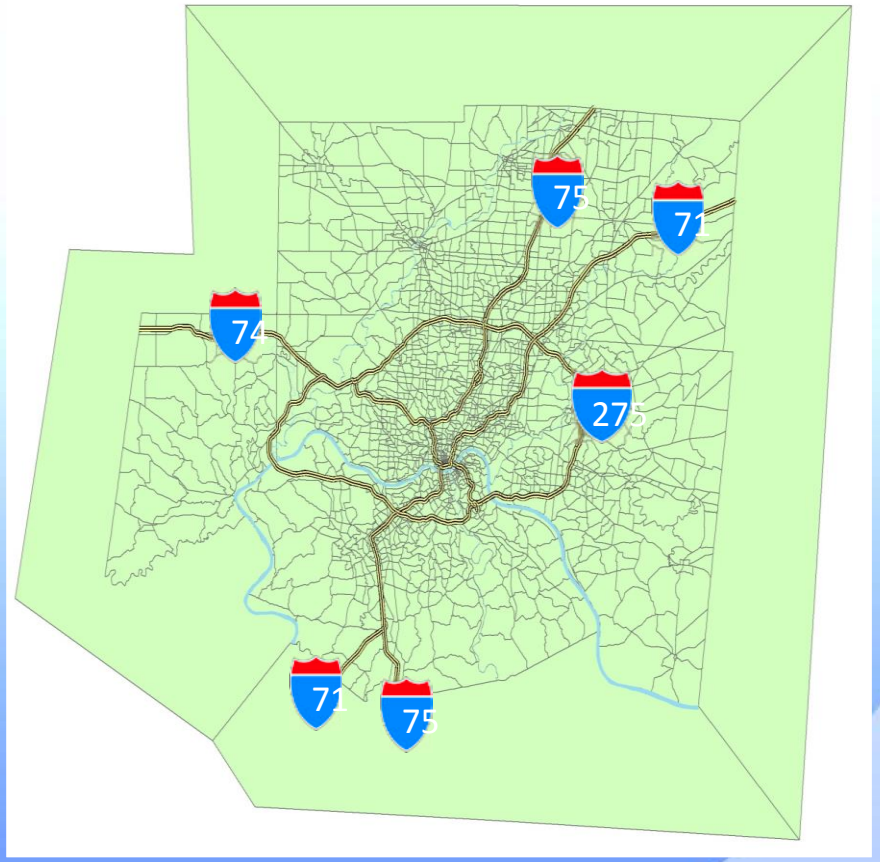
[3]

OKI experience with AirSage data

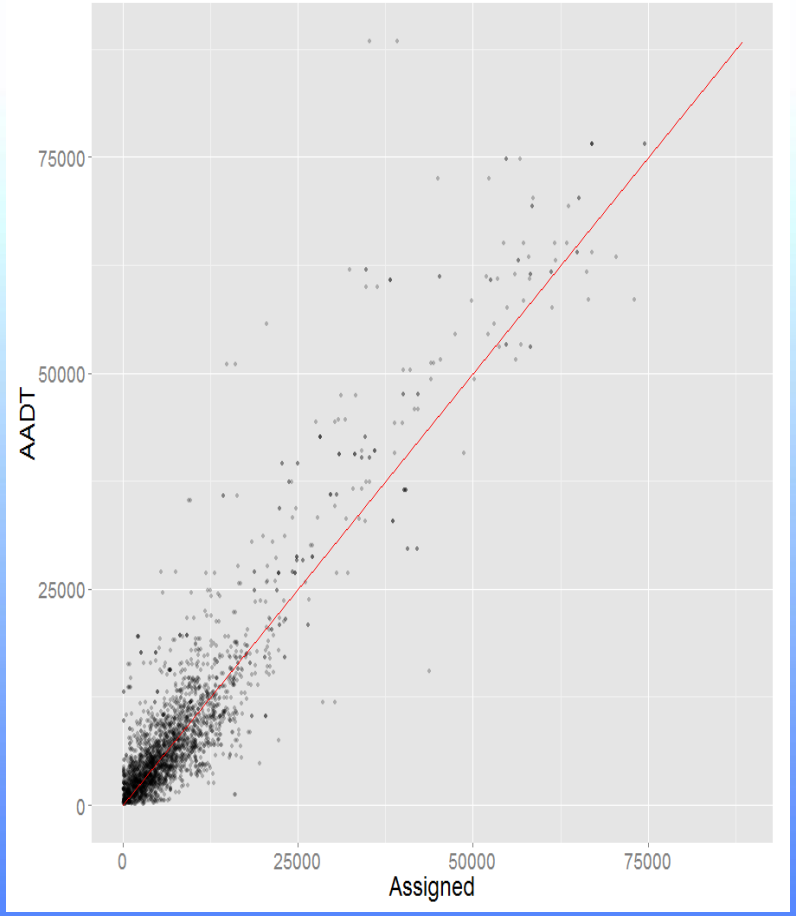
Andrew Rohne
OKI

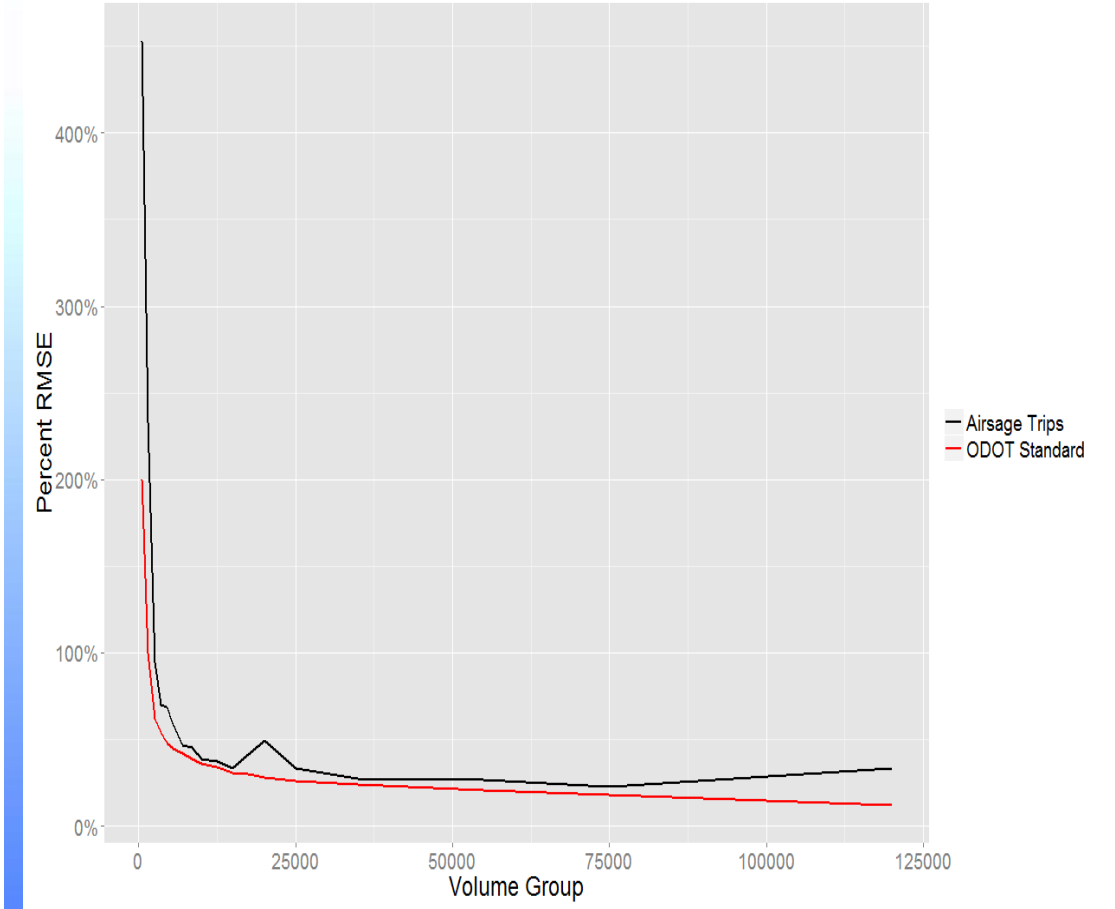
OKI Experience with Airsage Data (so far)

- Purchased:
  - Internal TAZs
  - Aggregated Externals
  - 24 Hour and AM Peak
  - Average Weekday in March 2012
- Compared Airsage vs. surveys and counts
  - Assigned the data to the network
  - Looked at trip length frequencies
  - Looked at county-county flow
  - Looked at the EE trips
- **Two data points – USE WITH CAUTION**



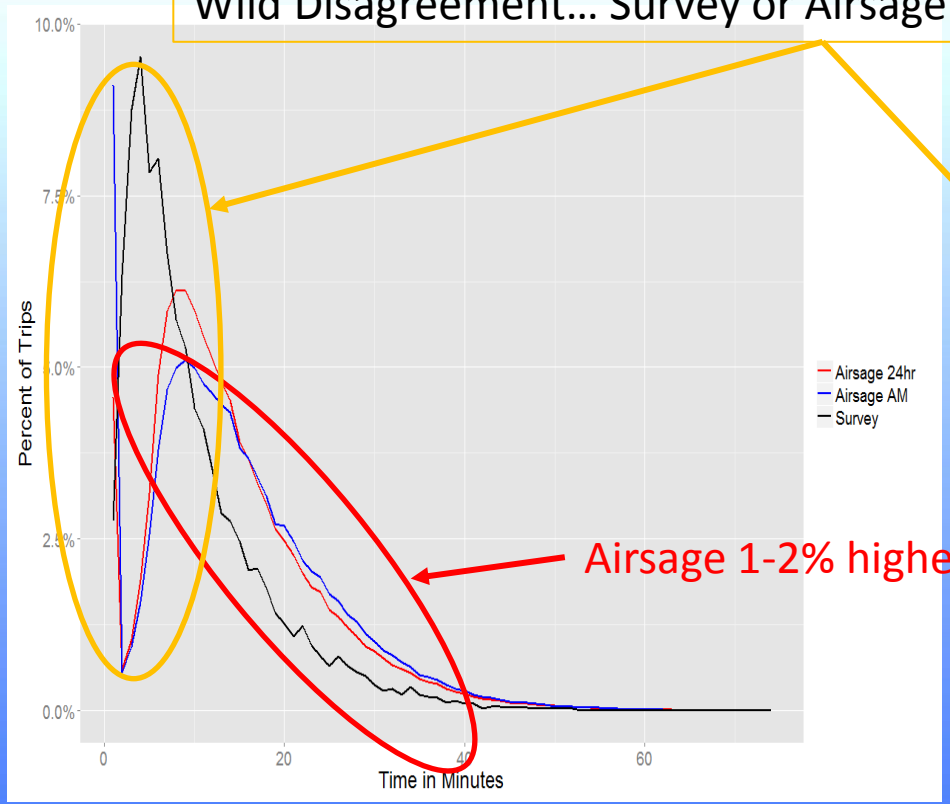
Assignment


75000
50000
25000
0
AADT
0
25000
50000
75000
Assigned

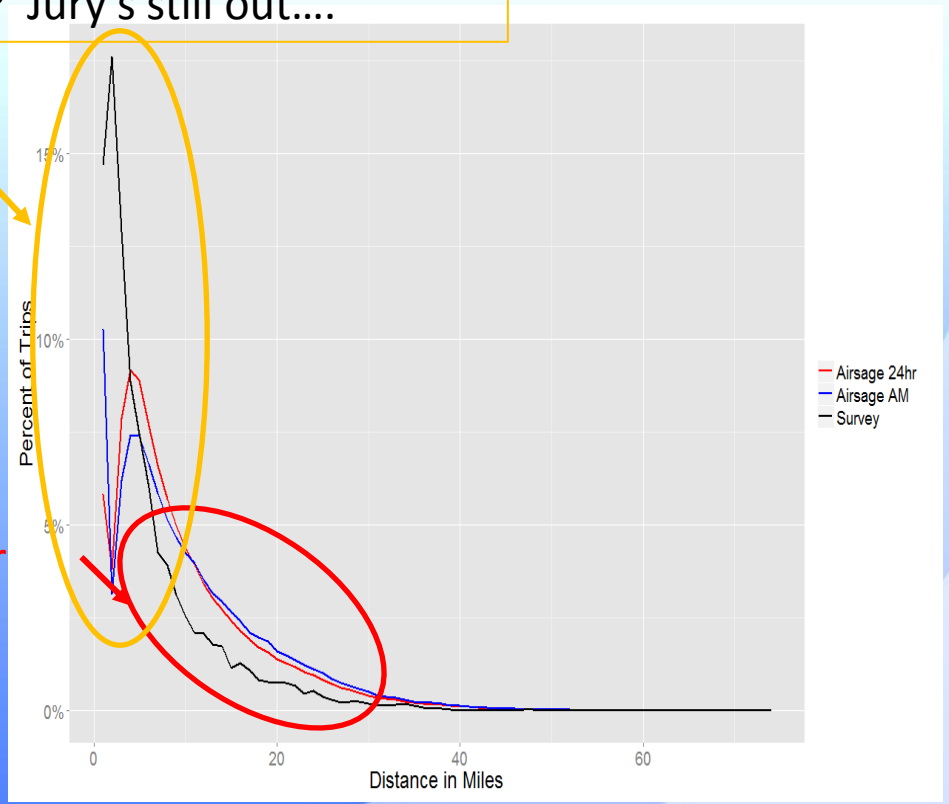

400%
300%
200%
100%
0%
Percent RMSE
0
25000
50000
75000
100000
125000
Volume Group
Airsage Trips
ODOT Standard

Trip Length Frequencies

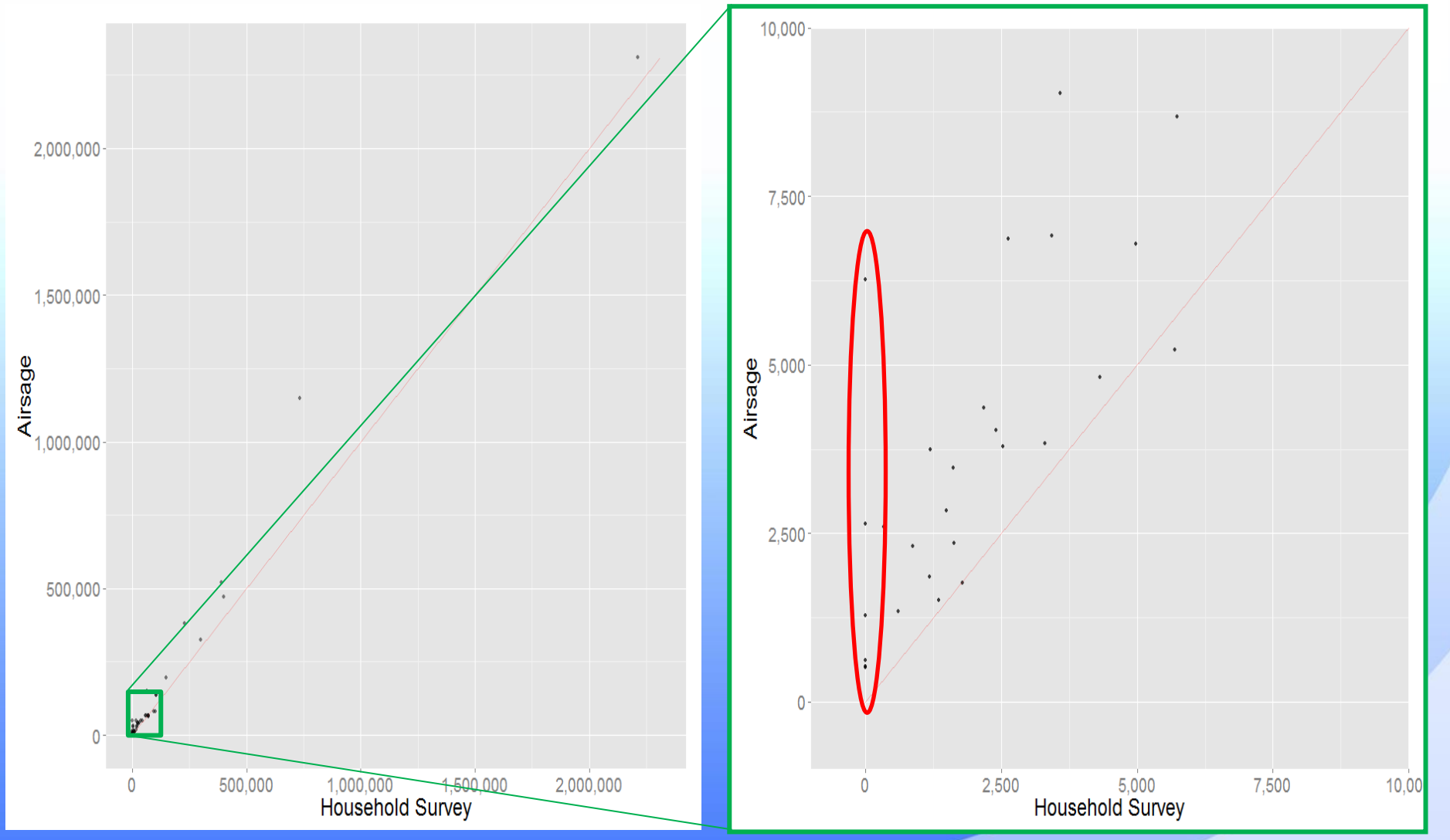
Wild Disagreement… Survey or Airsage? Jury's still out….



Airsage 1-2% higher



Airsage vs. Expanded HHTS



External Trips

	East	North	West	South	Internal
East		2%	0%	-1%	8%
North	-6%		-5%	-46%	21%
West	0%	0%		1%	9%
South	0%	1%	1%		9%
Internal	-6%	18%	-1%	-5%	

Andrew Rohne • arohne@oki.org • okiAndrew

[4]

Can you afford your traveling?

Rolf Moeckel
University of Maryland

Traditional land-use modeling

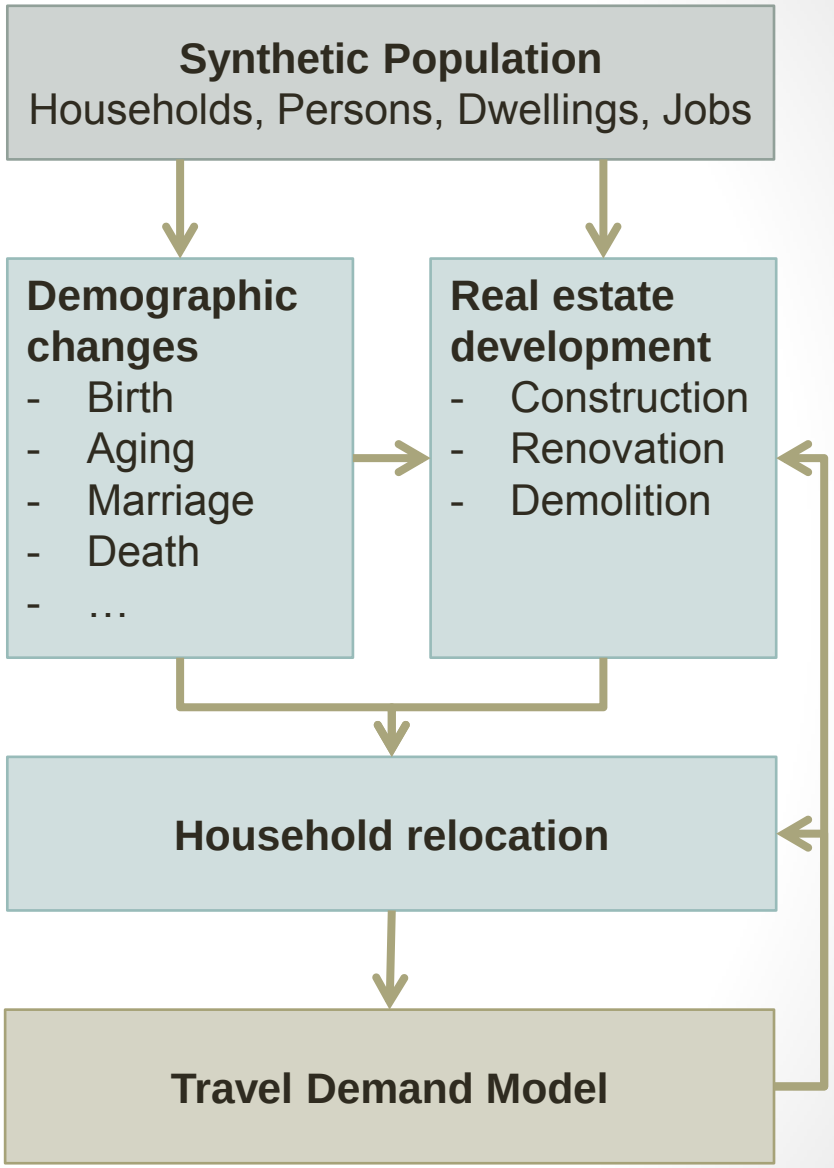
- Location choice is based on utilities

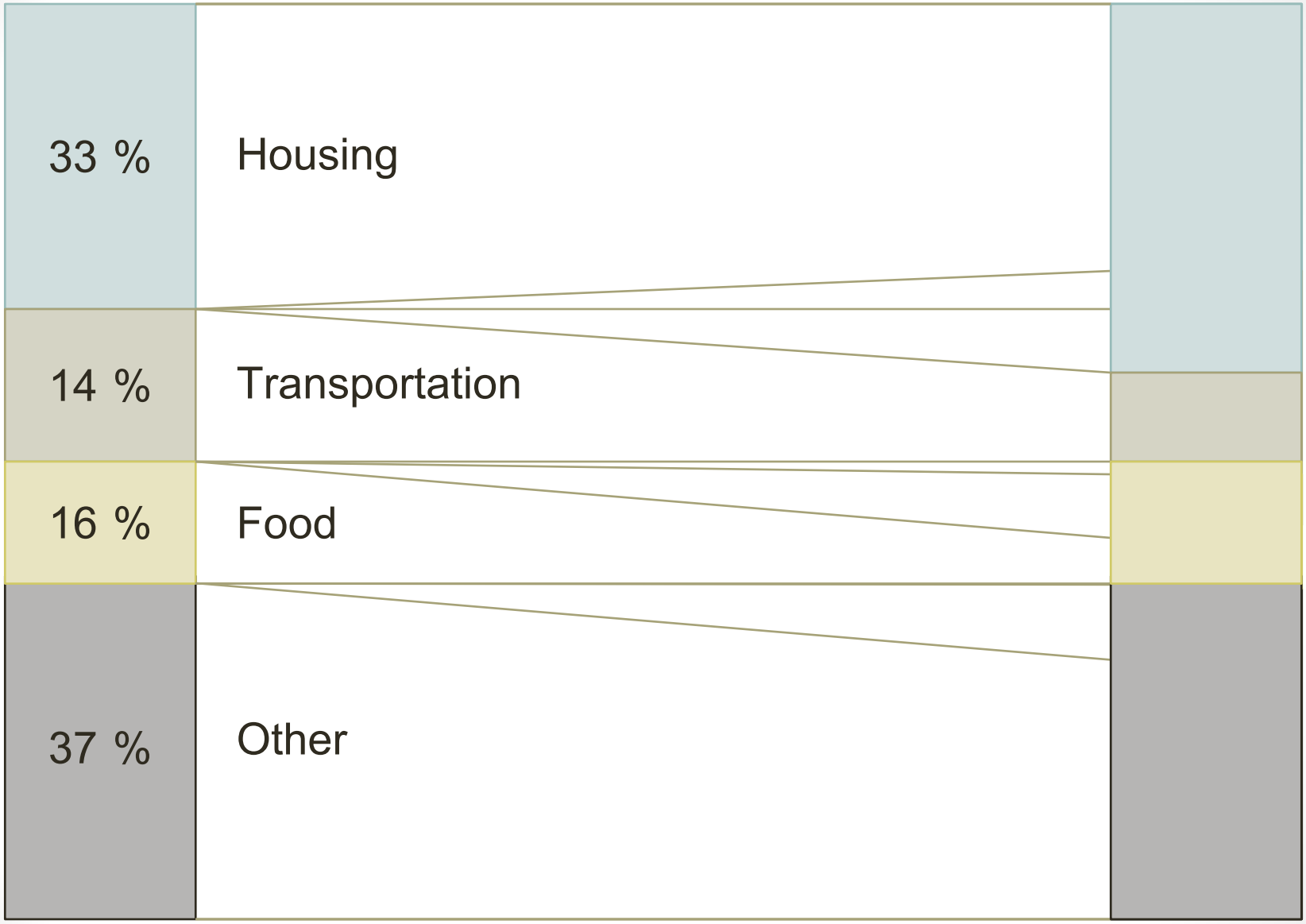
  $u_i = \alpha \cdot size_i + \beta \cdot price_i + \gamma \cdot location_i + \ldots$

- In reality, most choice are made under constraints
  - Price of dwelling
  - Travel costs
  - Parking availability
- Modeling is less about maximizing utilities, but satisfying needs.

SILO

- Microscopic land-use model
- Fully integrated with travel demand model
- Two implementations
  - Minneapolis/St. Paul
  - Maryland

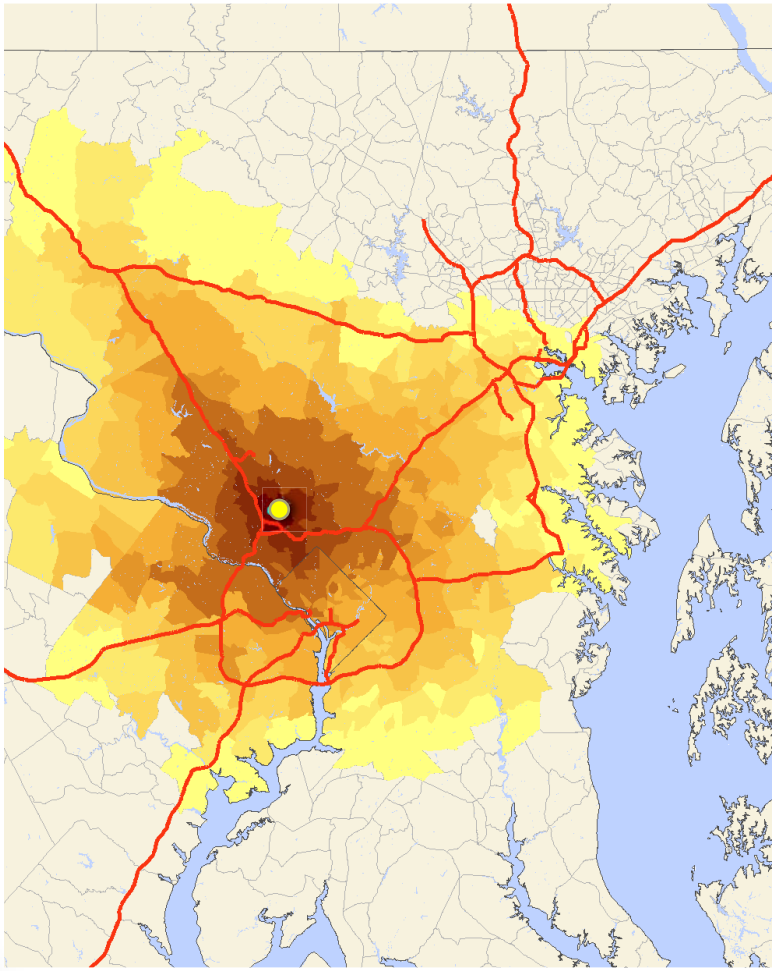


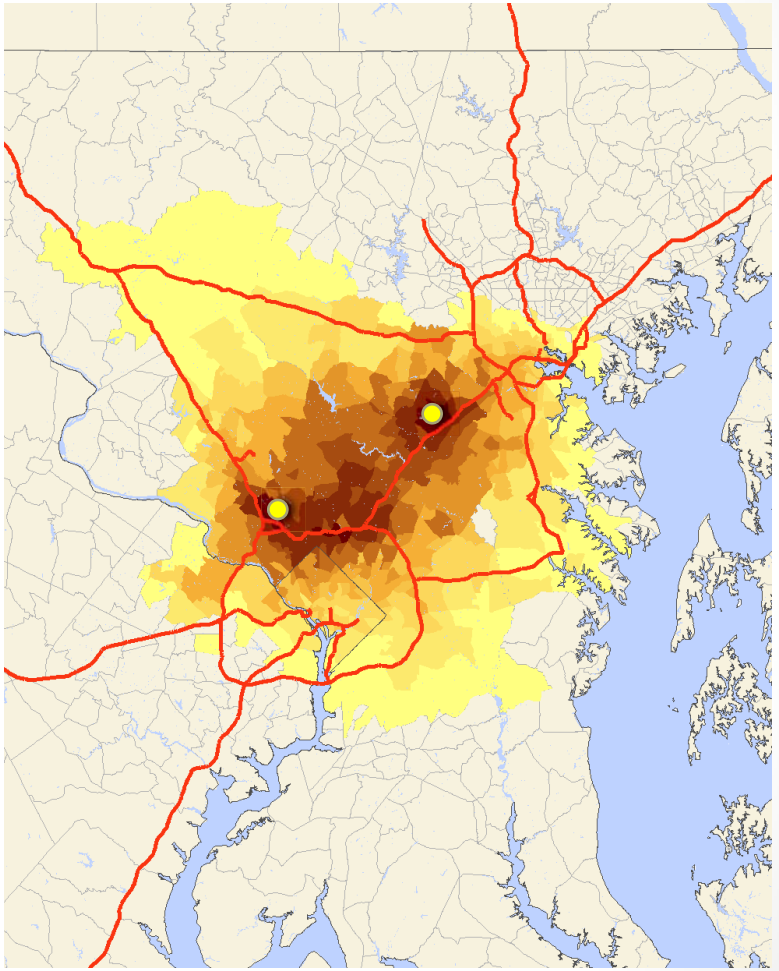


Compensate by cutting back other costs

Move to a less expensive neighborhood with lower transportation costs

Commute Travel Time





Implementation of constraints

- Replaceable location factors are added:

$$u_{replaceable} = a \times util_{size} + b \times util_{quality} + g \times util_{accessibility} + \ldots$$

- Essential location factors are multiplied:

$$u = u_{replaceable}^{\ a} \times u_{rent}^{\ b} \times u_{travelCosts}^{\ g} \times u_{commuteTime}^{\ d} \ldots$$

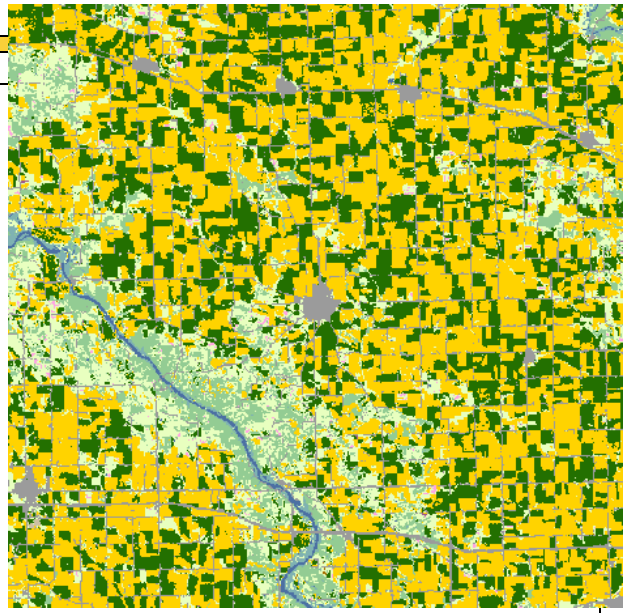
[5]

Enhancements to the MAFC freight model

Alan Horowitz
University of Wisconsin-Milwaukee

Major Steps: Crops

- Farm synthesis
  - Crop
  - Harvested acres
  - Location (long/lat)
  - Harvest dates
  - Planting dates
  - On-site storage
  - Truck ownership
- Farm shipment generation, by date
  - Number of shipments (random)
  - Size (random)
  - Truck type (random)
  - Destination type (elevator, ethanol, feed lot, etc.) (random)
  - Time of day (random)



Most of Cedar County, IA

Alan Horowitz, Maria Kurniati

Major Steps: Manufactured Products

- Shipments move from acutal establishment to actual establishment, perhaps through an actual transshipment point.
- Actual establishments within the region, "super-establishments" outside region
  - One super-establishment for each FAF zone for each 6-digit NAICS
- Producing establishments limited to those which produce the three (original) indicator industrial commodities
- Any establishment can be a potential consumer, per the Benchmark IO Table.
- No households
- No empties, originally

Alan Horowitz, Maria Kurniati

Major Steps: Manufactured Products

- Shipment Generation (random)
  - Size (random)
  - Mode (random)
  - Need one truck? Needs multiple trucks? (random)
- Destination Selection (random)
- Mode Choice, fixed shares (random)
- Tour Selection, fixed shares (random)
  - P-C, P-W—C, P—W-C, P-C-C, P-W-W-C, P-W—C-C, P—W-C-C, P-C-C-C
- Transshipment Point Selection (random)
- Time of Day Selection (random)
- Dynamic, multiday traffic assignment, point-to-point (deterministic)

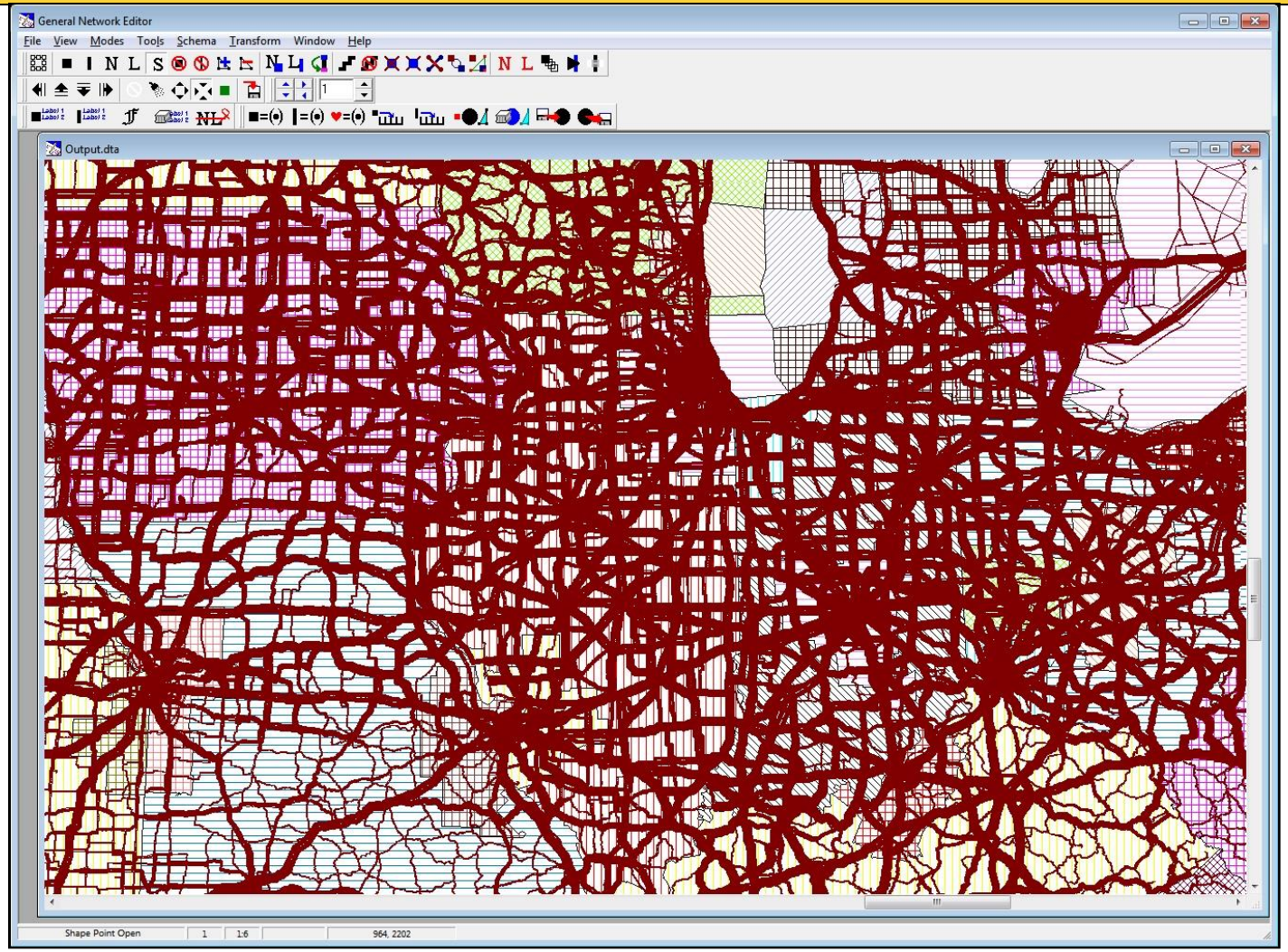
Alan Horowitz, Maria Kurniati

New Elements

- Upgrade from **Descriptive Model** to a **Planning Model**
- Increase from **5** to **27** specific commodities at 3-digit SCTG
- Multinomial logit **tour-choice** model, not fixed shares
- **Empties**, fixed shares (random)
- Commodity "enhancers" to **scale up** the results to match all trucks. (random)
- Assignment sensitivity to **time**, **distance**, **tolls**, and **hours of service rules**, including rest periods.

Alan Horowitz, Maria Kurniati

27 Commodities, 24 Hours



Alan Horowitz, Maria Kurniati

[6]

Synthetic household travel data from consumer and mobile phone data

Josie Kressner
Transport Foundry



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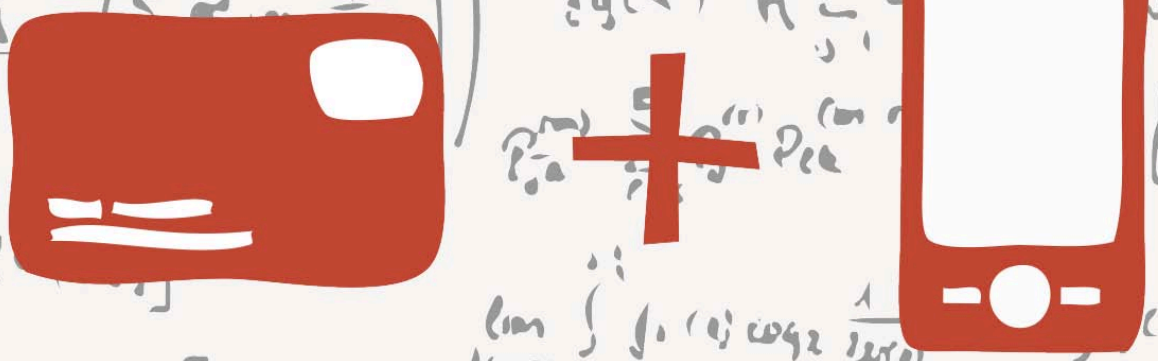

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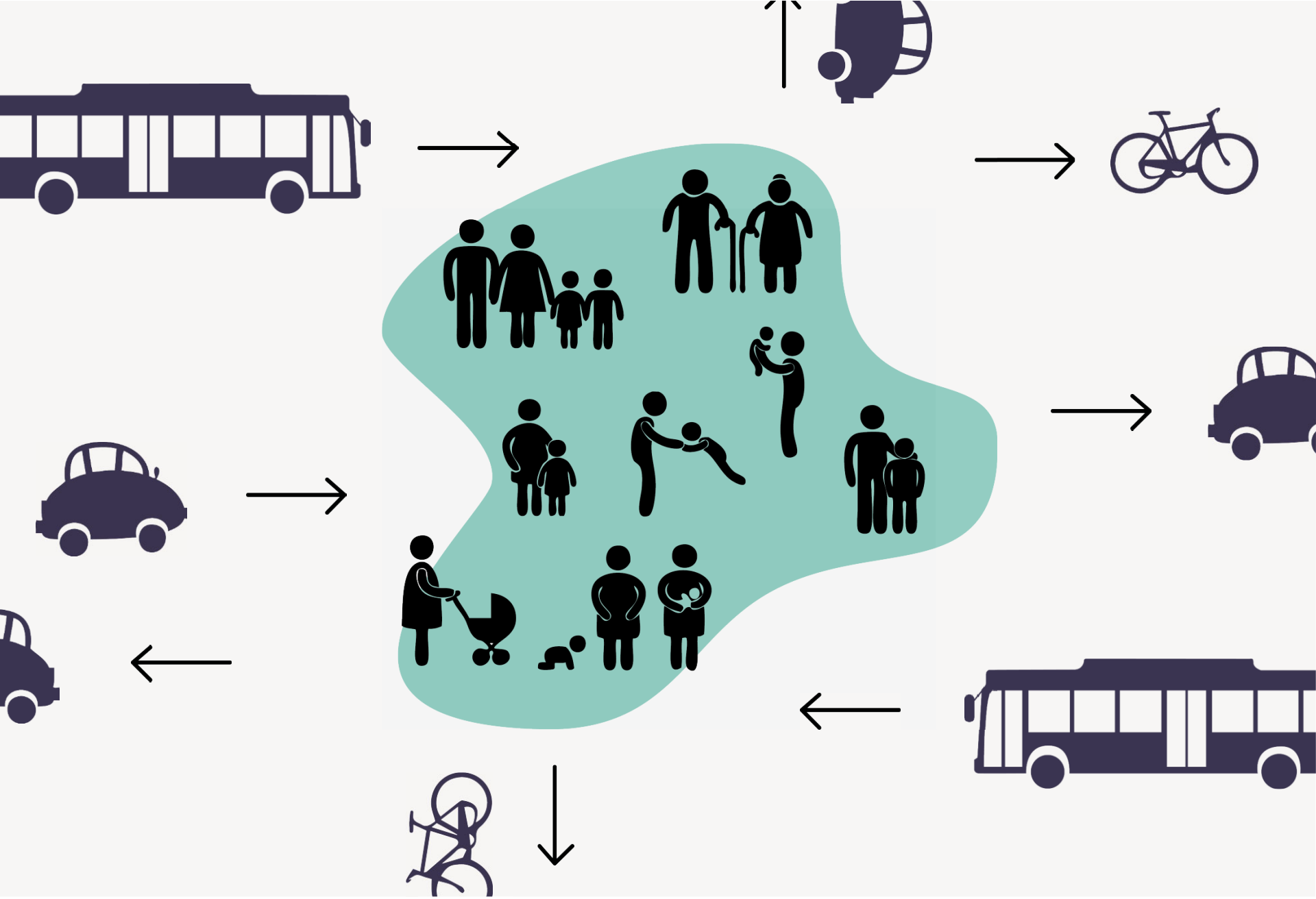

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[7]

FTA traffic assignment study

Ken Cervenka
Federal Transit Administration

FTA Traffic Assignment Study

- "Measuring Congestion Relief Benefits"
  - Of major transit projects (also applies to highway projects)
  - Initial research completed in 2004 (AECOM)
    - Yes, assignment convergence does matter
    - But, did not check accuracy of auto volumes and times
  - New research initiated in October 2011
    - Caliper Corporation selected as contractor
    - Review of current practices used by 30 largest MPOs found widespread deficiencies
    - Focus is on assessing and improving assignment & feedback practices (working with 5 MPO models)
    - Final report due December 2014

Challenge: Getting realistic auto travel times & project forecasts

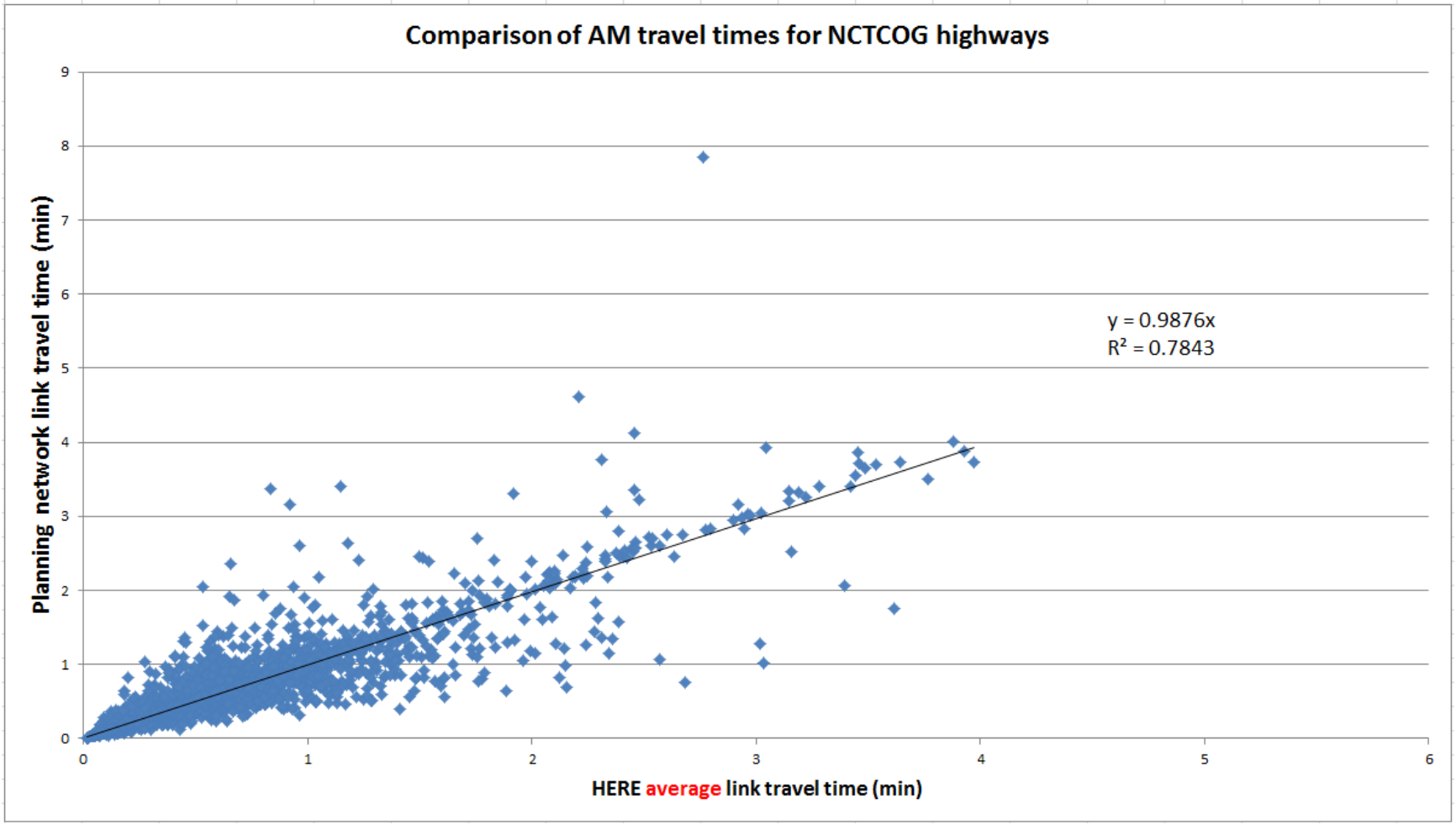
- Are the predicted travel times realistic?
  - An issue for static, DTA, or micro-simulation
  - Model calibration/validation (base) year
    - More than a trip length frequency distribution check
    - Check both counts and speeds
  - Forecasts
    - Are they plausible?
    - What are good practice assignment & feedback protocols?

Challenge: Good practices for highway assignments

- Accurate roadway coding & modeling
  - Value of spatial rectification to quickly find errors
  - Which links to include
  - Zone sizes and centroid connectors
  - Time-of-day directional capacity
  - Turn prohibitions and intersection delay
  - Volume-delay functions & free flow speeds

Challenge: data for validation

- Time-of-day, directional traffic counts
  - How many are needed?
  - Quality control approaches to ensure usability
- Time-of-day auto travel times
  - FHWA's "National Performance Management Research Data Set" (HERE data for NHS)
  - More comprehensive HERE Traffic data
  - Recurring versus non-recurring congested times


Comparison of AM travel times for NCTCOG highways
Planning network link travel time (min)
HERE average link travel time (min)
y = 0.9876x
R² = 0.7843
0
1
2
3
4
5
6
7
8
9

[8]

Modeling the rise of car sharing

Eric Petersen
HDR

Intriguing issues raised by car sharing

- Should 0 car households be considered “captive” in traditional models?
- Are observed differences in auto ownership rates merely a reflection of urban lifestyle/density?
- Does car sharing membership lead to a measurable decrease – or increase – in travel compared to other car constrained households?
- Will these changes (lower car ownership) persist after young adults enter another life-cycle phase?

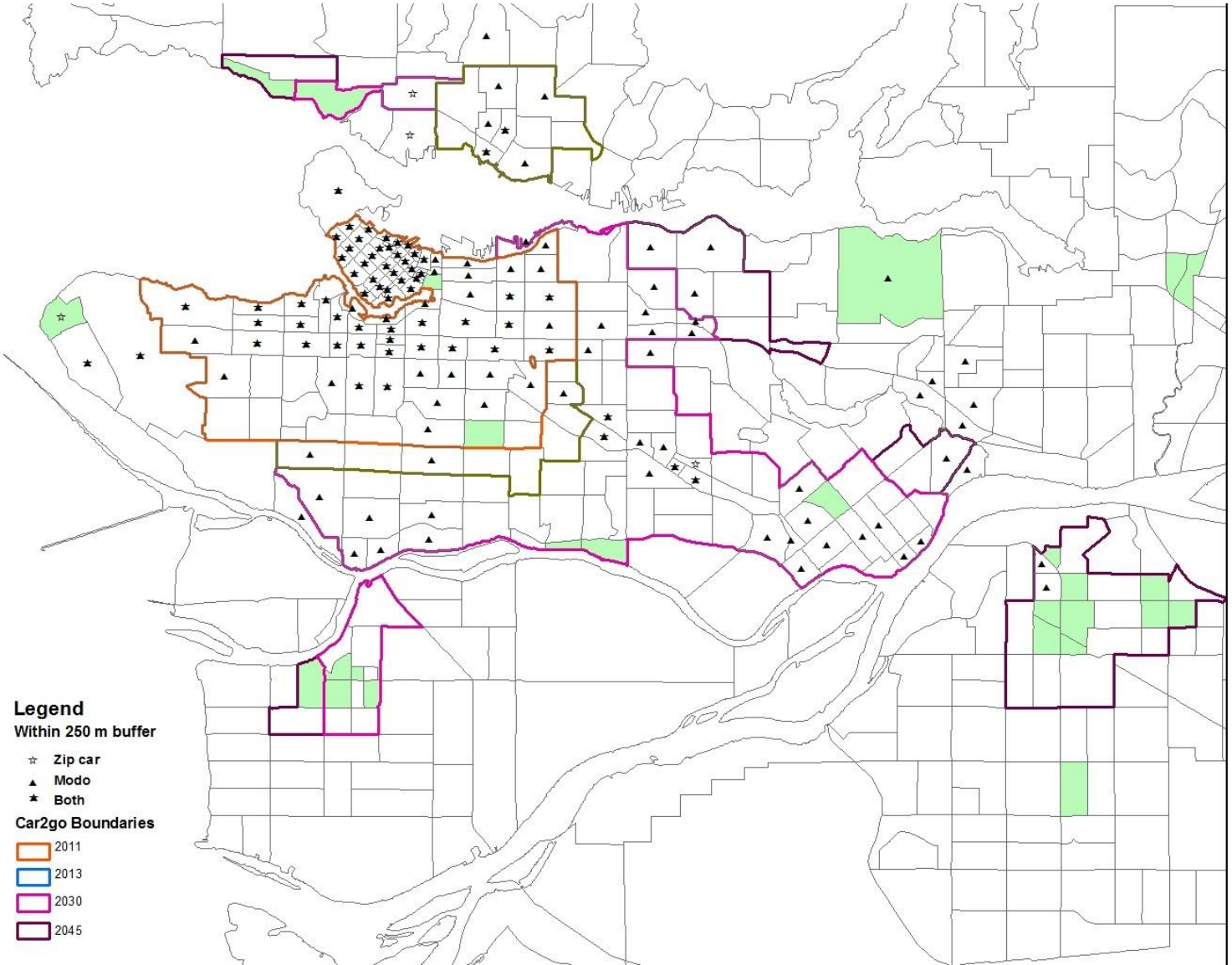
Preliminary data availability

- 2011 trip diary for Metro Vancouver did not probe on car sharing arrangements
  - 700 observed trips were made by auto drivers from 0 car HHs (thus not “captive”).
- Future surveys will probe the use of company cars and membership in car sharing services when car driven by “captive” HH member
  - Pilot survey being conducted in Metro Vancouver over 2014-2015.

Preliminary work (models)

- Geographic proximity calculated at zonal level.
  - 250m and 500m buffers drawn around car share lots
- Proximity to car sharing sites significant for car ownership and mode choice models even after controlling for:
  - transit accessibilities
  - zone density
  - household income
  - household size
  - workers in household

Car-sharing services in Metropolitan Vancouver (2011 and beyond)



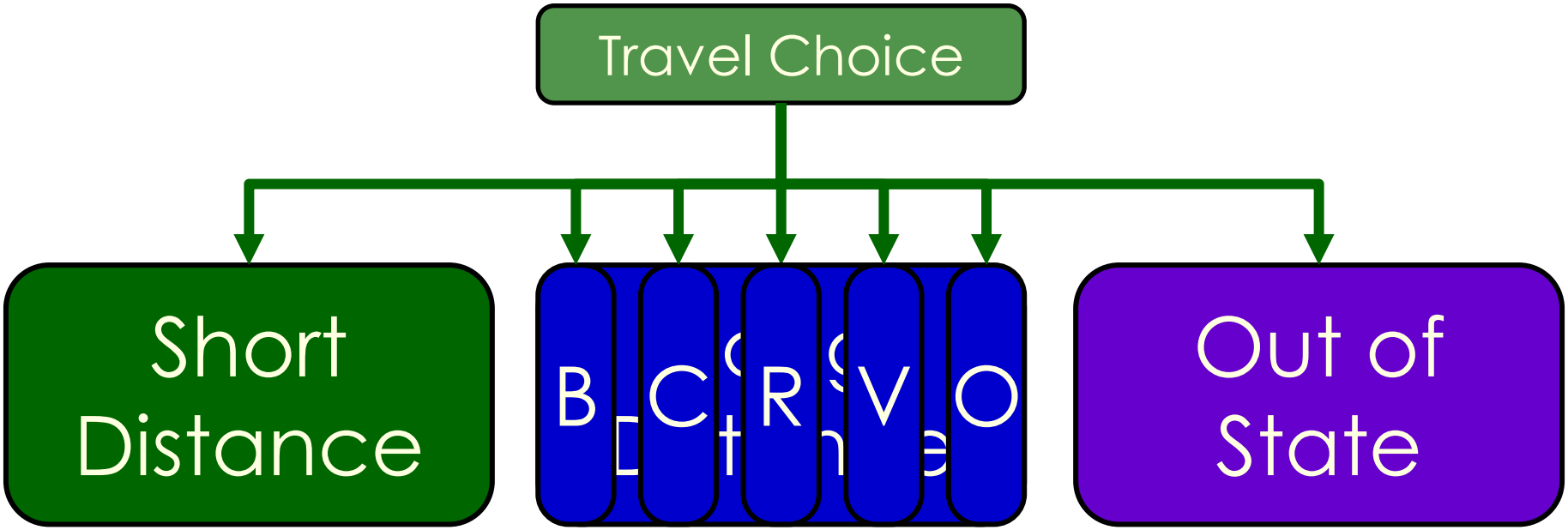
Future steps

- Compare trip rates of members and non-members of car sharing services.
- Construct a simultaneous model of car ownership, car sharing membership and monthly/annual transit pass holding
- Future targeted surveys to determine how frequently return leg is not completed using car sharing
  - i.e. does car sharing introduces uncertainty about consistency of mode choice for entire tour?

[9]

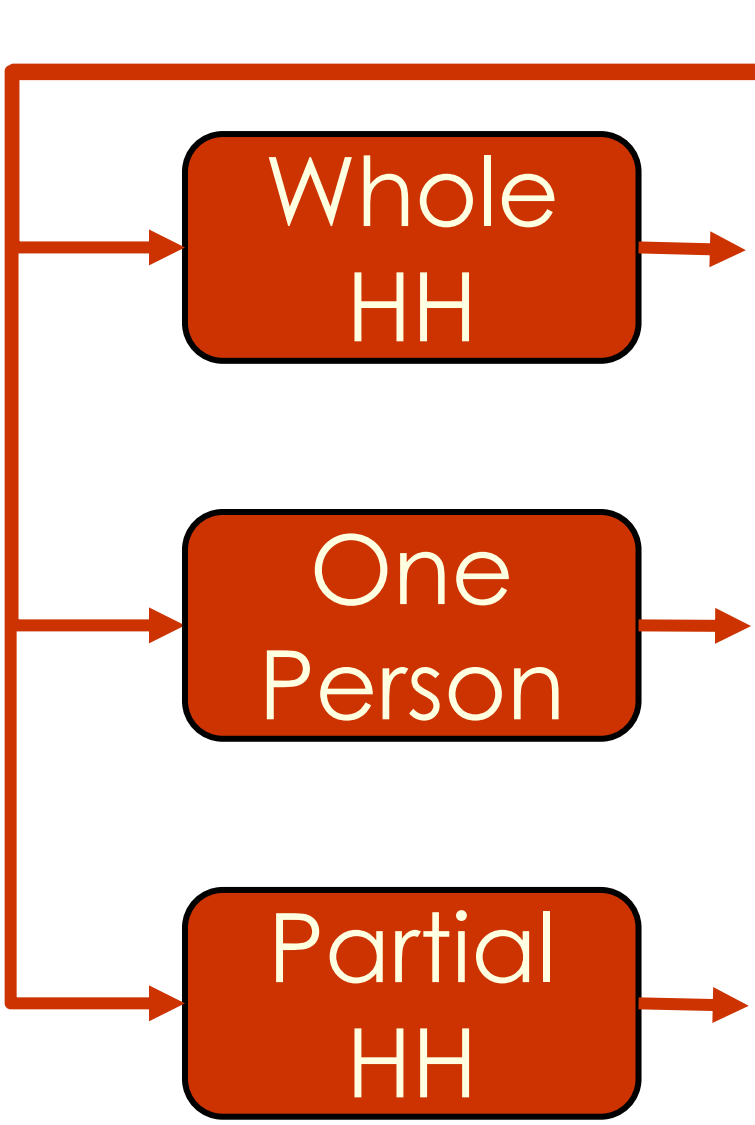
California's long distance personal travel model

Kevin Stefan
HBA Specto



Business
Commute
Recreatio
n
VFR
Other

Who goes there?



Group tour with entire HH created
Nobody is short distance

Model selects single traveller
Everybody else is short distance

Model selects party size
Model selects "primary" traveller
Party filled randomly from remaining members
Everybody left are short distance

Travel Choice
Party Type
Party Formation

Tour Duration

Trip Direction

Time Of Day

Destination

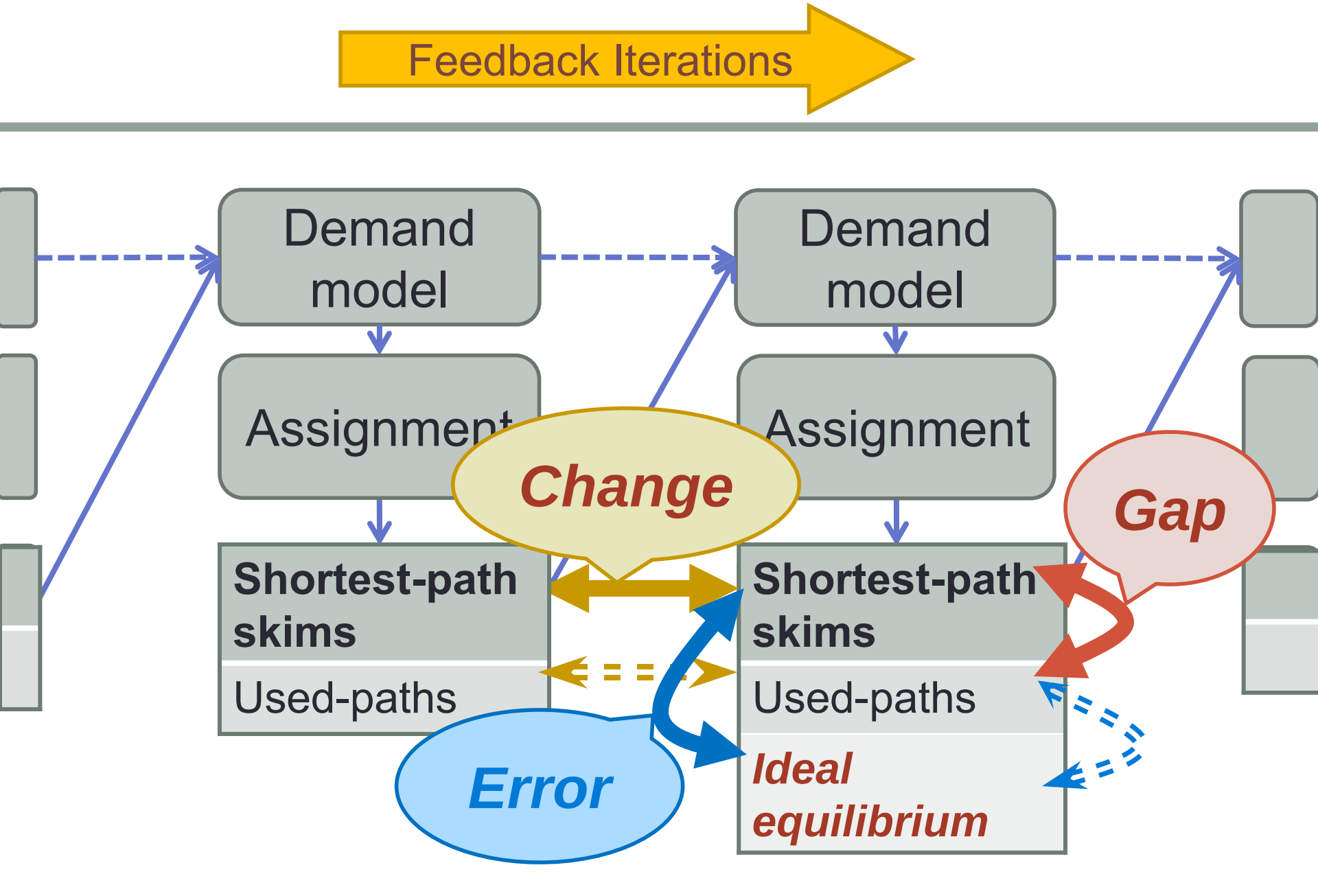
Main Mode

Access / Egress Mode

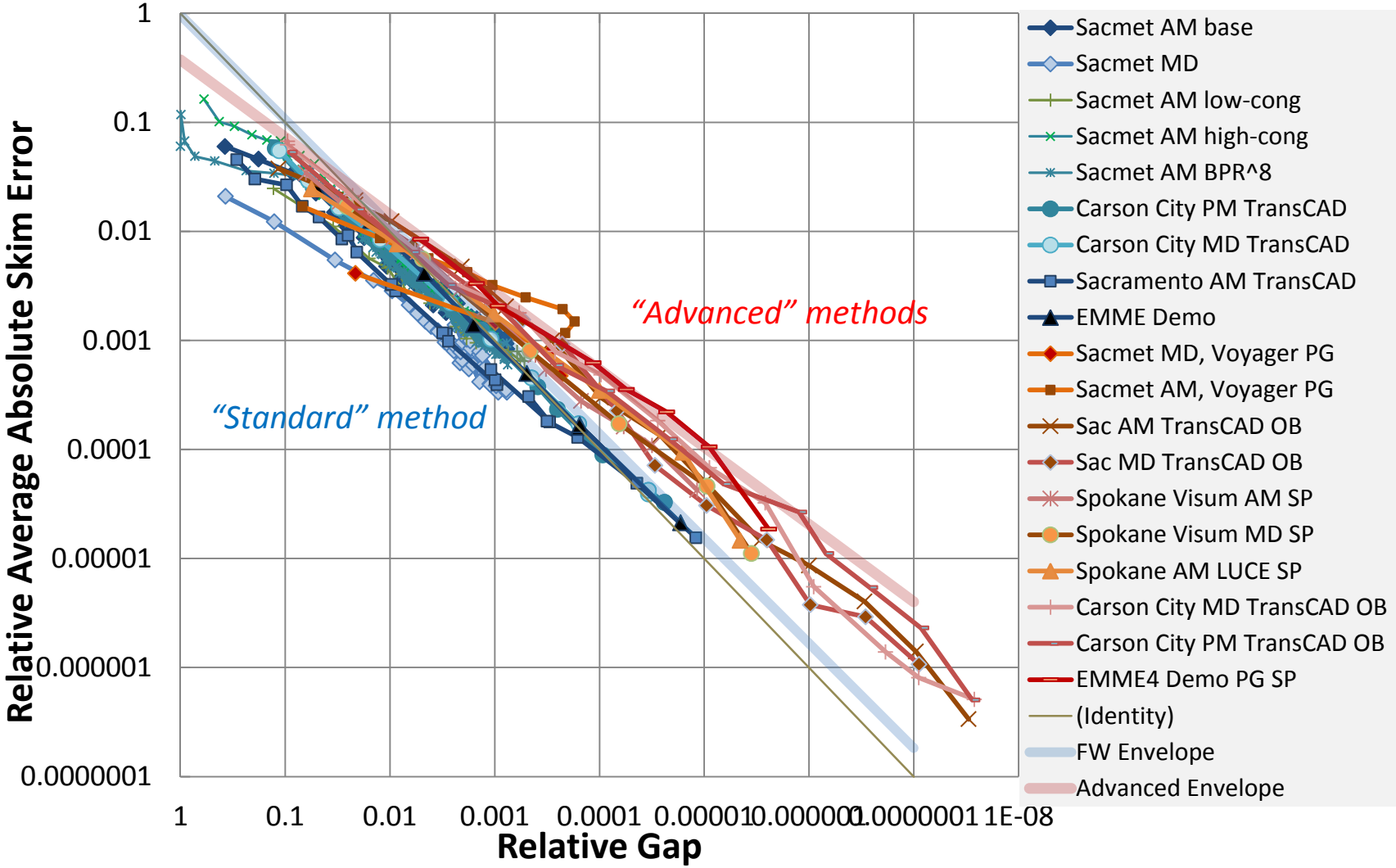
[10]

Converging feedback assignments enough, automatically

John Gibb
DKS Associates


Feedback Iterations
Demand model
Demand model
Assignment
Assignment
Change
Gap
Shortest-path skims
Used-paths
Shortest-path skims
Used-paths
Error
Ideal equilibrium

Skim Error – Relative Gap relations

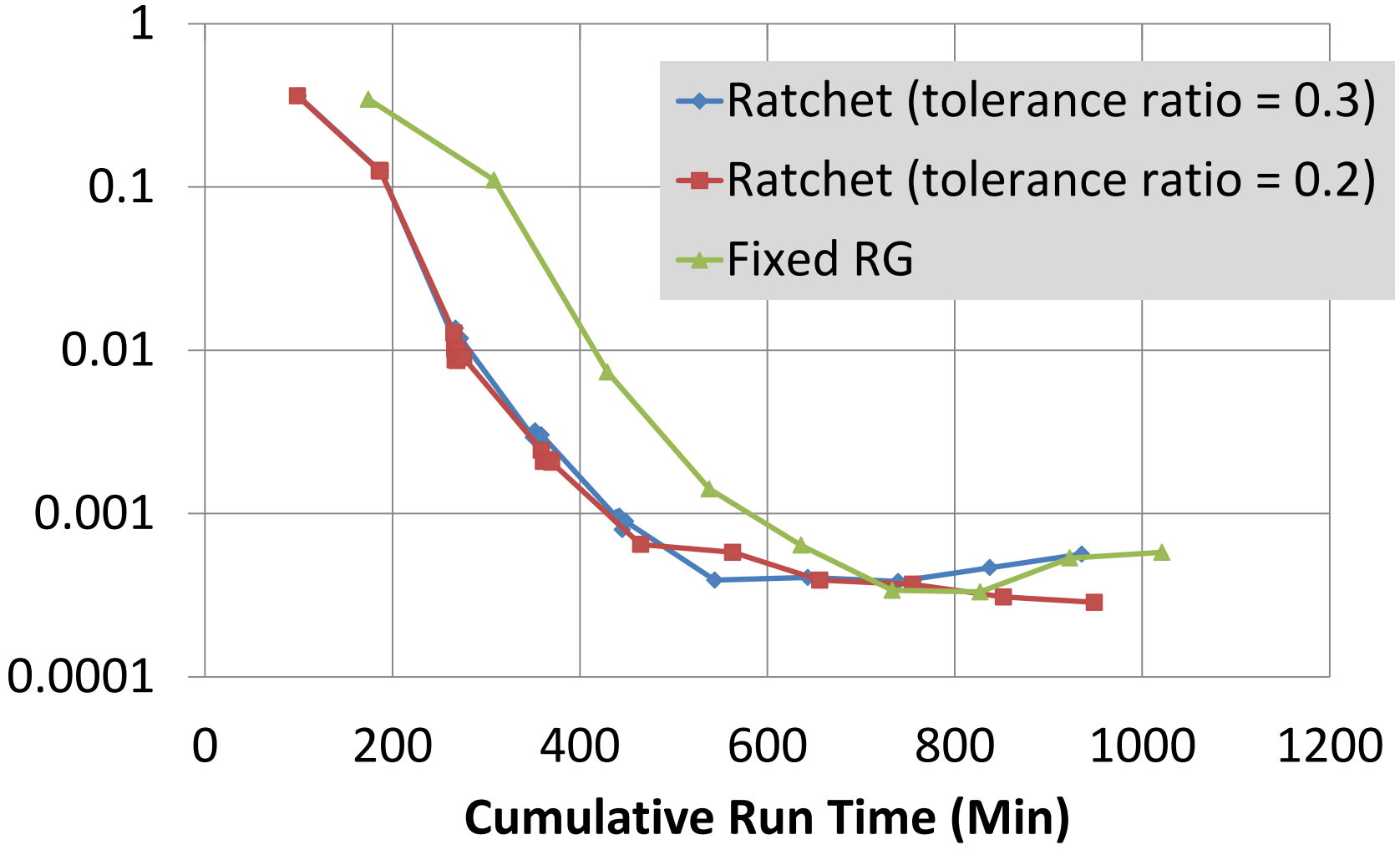


Feedback loop

- Demand Model

- Assignments
- Skims

Relative Skim Time Change



[11]

Cellphone Location Data to Complement Household Travel Surveys

Krishnan Viswanathan
CDM Smith

Data Layout

	timestampMs	latitudeE7	longitudeE7	accuracy	activitys
1	1398548888684	305465808	-842329692	30	list(timestampMs = "1398548794930", activities = list(list(type = "still", confidence = 100)))
2	1398548603655	305465641	-842329392	39	list(timestampMs = "1398548615914", activities = list(list(type = "still", confidence = 100)))
3	1398548301576	305465670	-842329408	39	list(timestampMs = c("1398548174994", "1398548301924", "1398548436065"), activities = list(list(type = "still", confidence = 1
4	1398548013731	305465703	-842329276	39	list(timestampMs = "1398548055971", activities = list(list(type = "still", confidence = 100)))
5	1398547933641	305465703	-842329276	39	list(timestampMs = "1398547936823", activities = list(list(type = "still", confidence = 100)))
6	1398547871801	305465738	-842329311	39	NULL
7	1398547801551	305465597	-842329610	36	list(timestampMs = "1398547804838", activities = list(list(type = "still", confidence = 100)))
8	1398547716516	305465164	-842329229	24	NULL
9	1398547626093	305465564	-842329473	11	list(timestampMs = "1398547658816", activities = list(list(type = "still", confidence = 100)))
10	1398547580161	305465539	-842329434	15	NULL
11	1398547534714	305465823	-842329305	38	list(timestampMs = "1398547537937", activities = list(list(type = c("still", "inVehicle"), confidence = c(92, 7))))

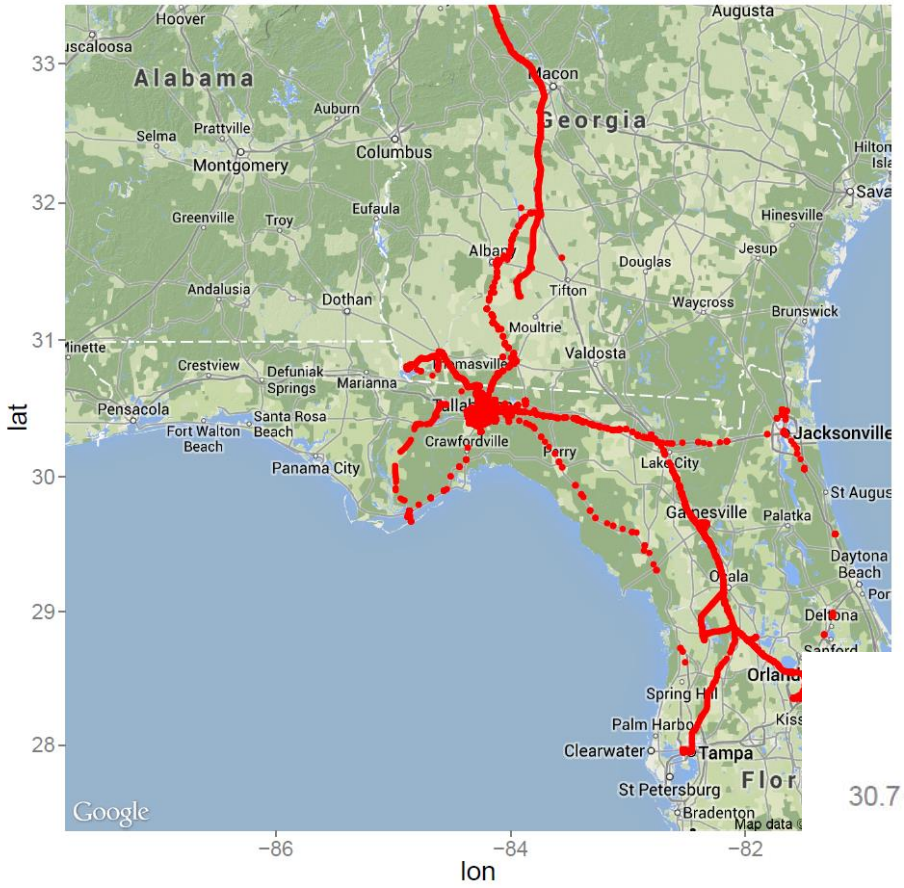
	t	lat	lon	accuracy	activity	confidence	velocity	altitude	heading
1	1398548889	30.54658	-84.23297	30	still	100	NA	NA	NA
2	1398548604	30.54656	-84.23294	39	still	100			
3	1398548302	30.54657	-84.23294	39	still	100			
4	1398548014	30.54657	-84.23293	39	still	100			
5	1398547934	30.54657	-84.23293	39	still	100			
6	1398547872	30.54657	-84.23293	39	NA	NA			
7	1398547802	30.54656	-84.23296	36	still	100			
8	1398547717	30.54652	-84.23292	24	NA	NA			
9	1398547626	30.54656	-84.23295	11	still	100			
10	1398547580	30.54655	-84.23294	15	NA	NA			
11	1398547535	30.54658	-84.23293	38	still	92			
12	1398547475	30.54665	-84.23297	31	NA	NA			
13	1398547401	30.54670	-84.23300	45	NA	NA			
14	1398547339	30.54685	-84.23301	32	inVehicle	34			

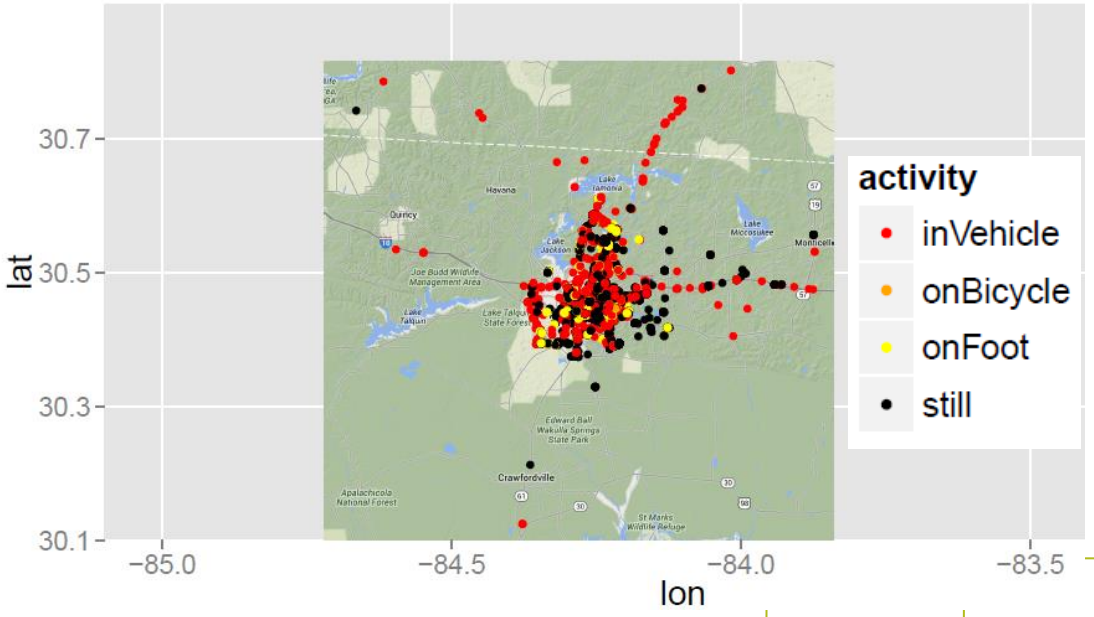
Variable	Frequency	Percent
n	874774	[redacted]
missing	0	[redacted]
unique	8	[redacted]
exitingVehicle	66	0%
inVehicle	6451	1%
NA	554767	63%
onBicycle	34	0%
onFoot	3506	0%
still	281442	32%
tilting	21575	2%
unknown	6933	1%

Data Source: Krishnan Viswanathan Personal Location Data

CDM Smith

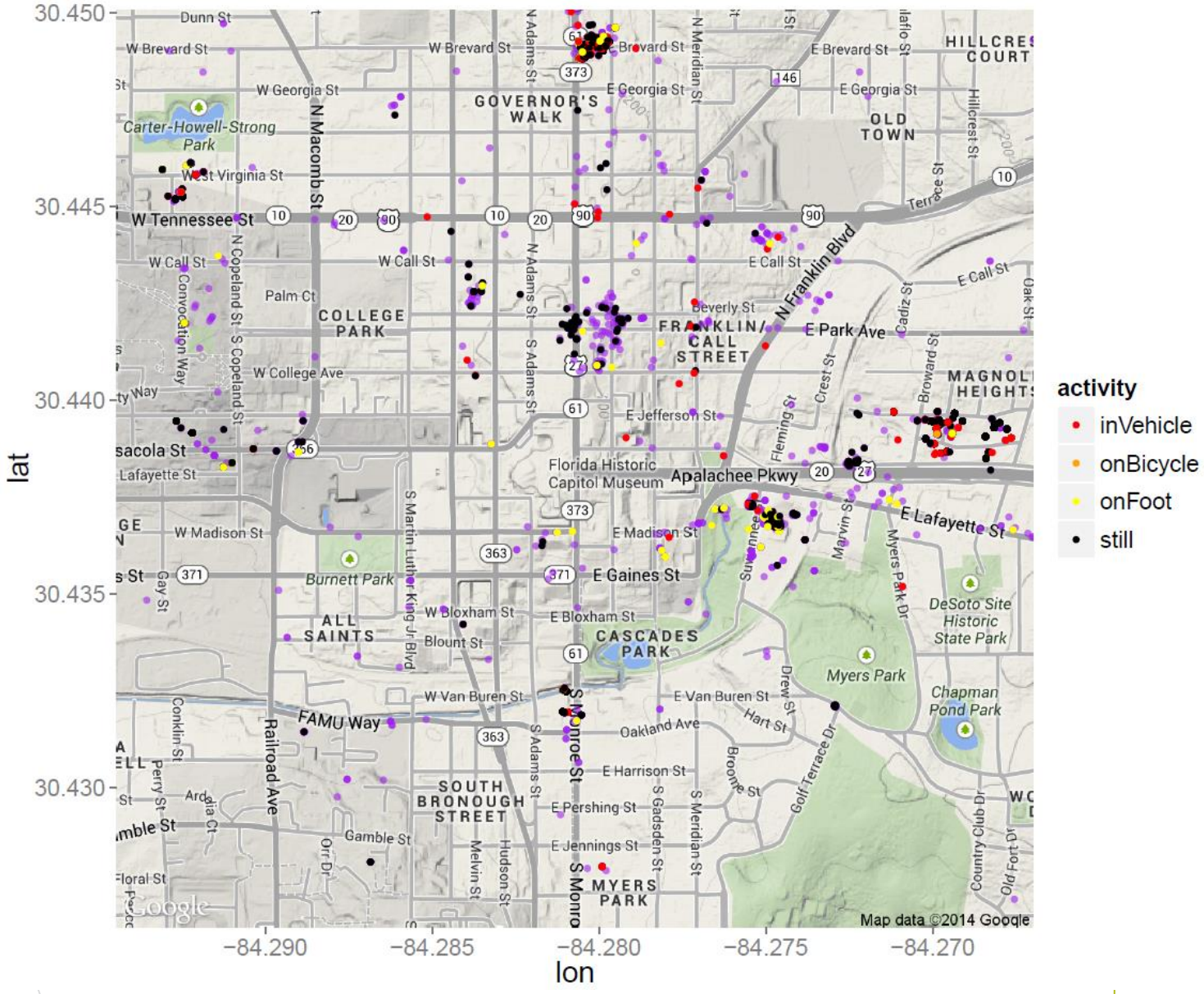
Inferred Modes – Long Distance & Regional





CDM Smith

Inferred Modes - Local



Summary and Next Steps

- Reduced Respondent burden
- Ability to get data for long distance and local trips
- Overlay with landuse data to infer purpose
- More insights needed on some of the metrics used in JSON file
- More data cleanup needed
- Privacy concerns

[12]

Making travel models better predictive tools

Tom Rossi
Cambridge Systematics

How We Validate Travel Models

- Comparing “base year” model outputs to observed data
- Reasonableness checks
- Sensitivity testing
  - Checks with changed inputs
  - Forecast year runs
  - Backcasts
  - Short term forecasts

CAMBRIDGE SYSTEMATICS

Backcasting

- Observed data for a year before the “base year” generally available *BUT* gaps cannot be filled
- Model input data also available *BUT* may not be organized for use in current model
  - » Geographic segmentation (zones)
  - » Highway network changes
  - » Transit system changes
- Changes in travel demand in “opposite direction” from forecasting applications

CAMBRIDGE SYSTEMATICS

Short Term Forecasting as Part of Validation

- Forecasting from the “base year” to a year that has happened (e.g. 2005 to 2010)
- Observed data may be able to be collected
- Model input data can usually be assembled (except when “too recent”)
- Changes in travel demand in “correct” direction

CAMBRIDGE SYSTEMATICS

FHWA Research Project

- Working with OKI and BMC
- Comparing results of "base year," backcast, and short term forecast model runs
- What works? in forecasting
- Creating a template for other agencies to take up challenges and add to body of knowledge
- Goal for FHWA TMIP is to understand how much model results are off and to communicate this uncertainty
- Question for you: What types of results from our analysis would be most helpful?

CAMBRIDGE SYSTEMATICS

[13]

Innovative TransModeler developments

Dan Morgan
Caliper Corporation

TransModeler 3.0's Innovative Features

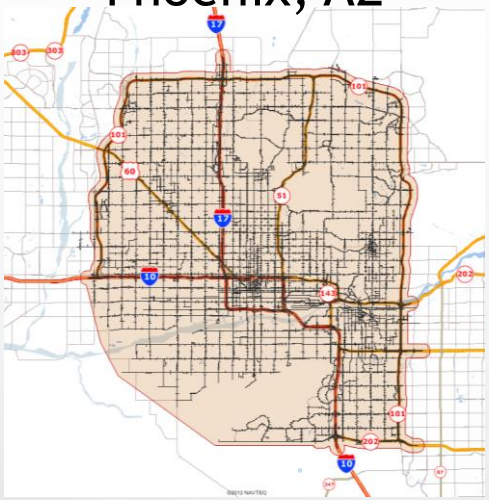
Two-way Left Turn Lanes

Passing on 2-lane Highways

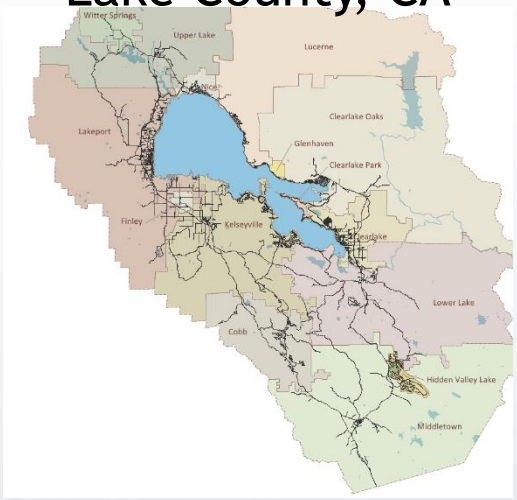
Reversible Lanes

Innovative Projects in TransModeler 3.0

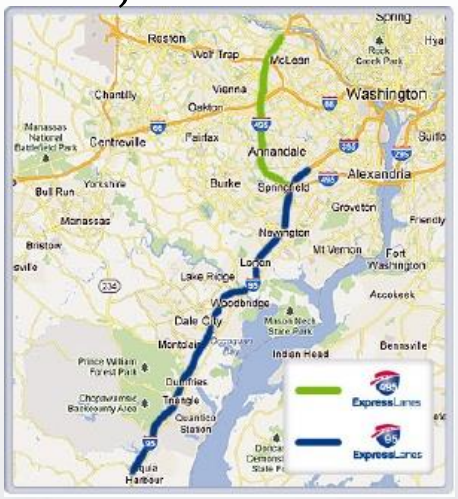
Phoenix, AZ



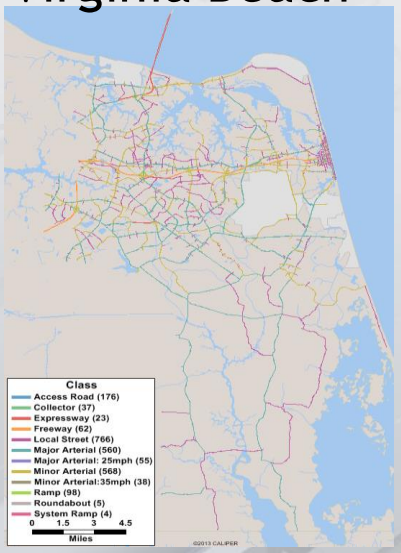
Lake County, CA



I-95, Northern VA

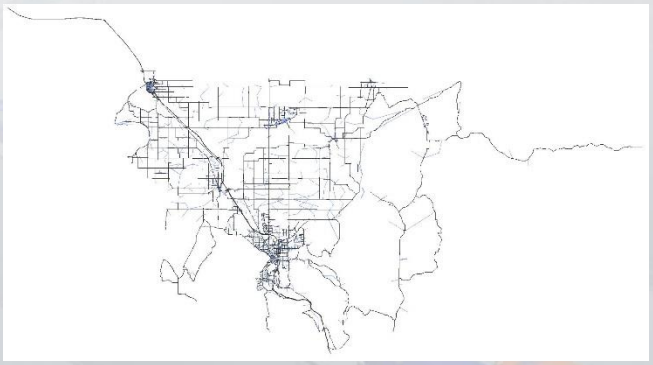


Virginia Beach



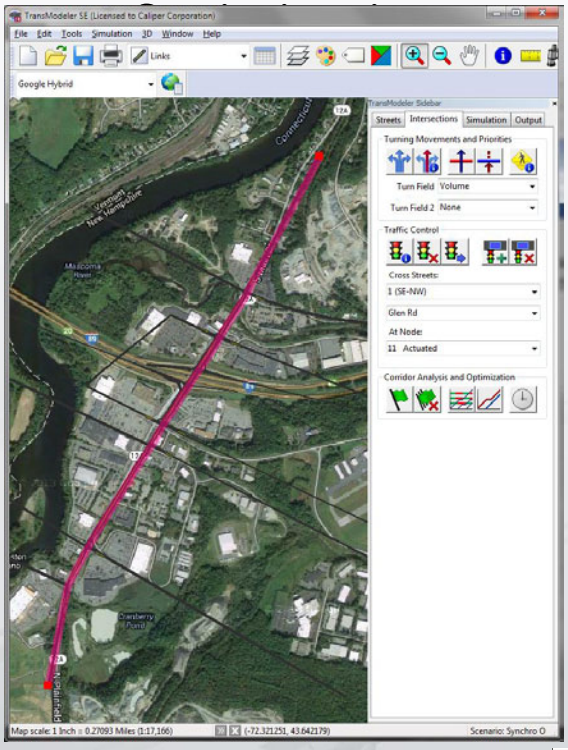
Orange County, CA

Whatcom County, WA

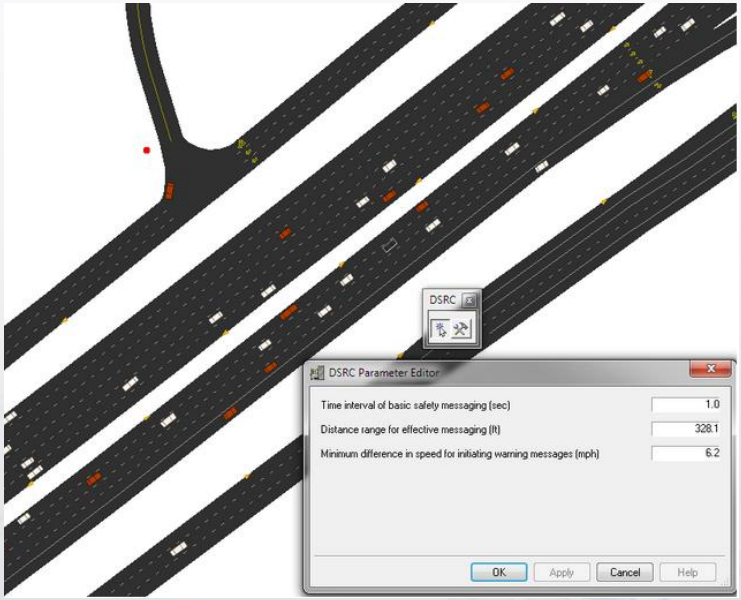


Innovative Developments in TransModeler 4.0

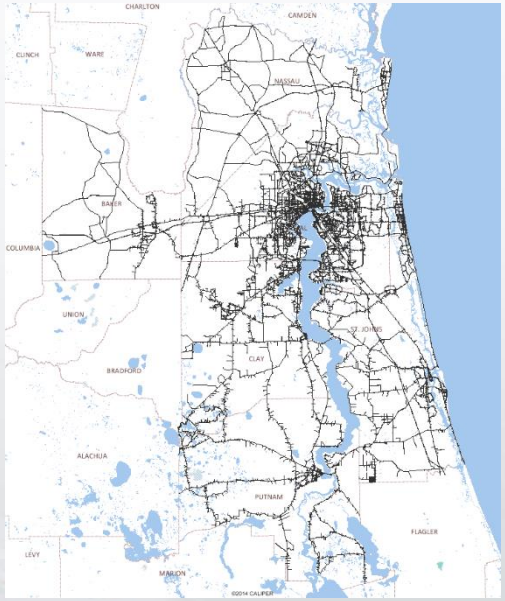
Simulation-based Traffic Signal



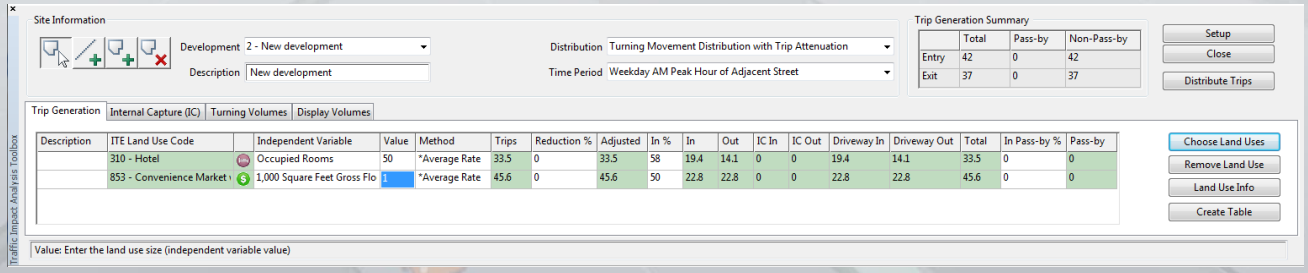
API Enhancements for Connected Vehicles



ABM Integration Enhancements



Complete Toolbox for Traffic Impact Analysis



Caliper

Introducing TransModeler SE

Caliper

www.caliper.com

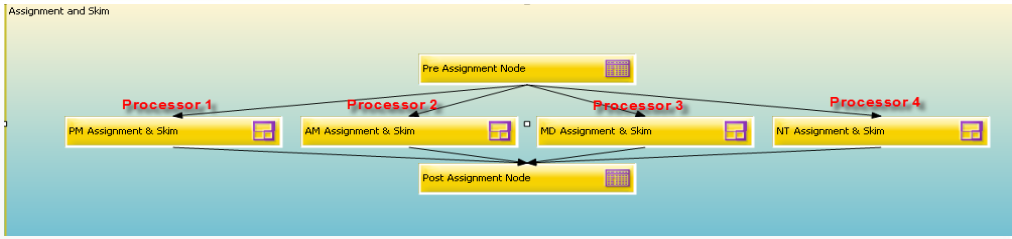
[14]

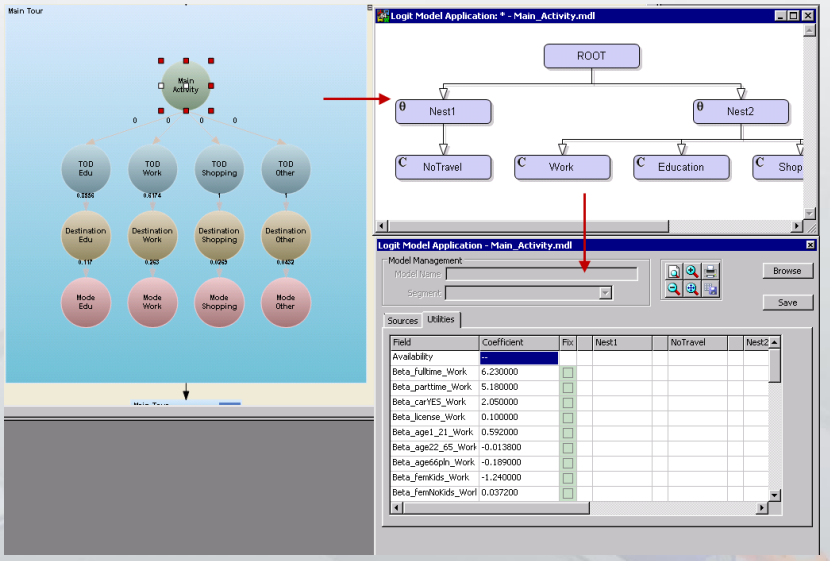
New features in TransCAD 6 & 7

Jim Lam
Caliper Corporation

High Performance Computing

- 64-bit computing
- More threaded processes & procedures
- Fully-threaded matrix operations
- Distributed and parallel processing with
- TransCAD compute engines
- Much faster transit assignments
- Even faster UE assignment routines, especially for turn penalties
- New nested logit application/estimation engine

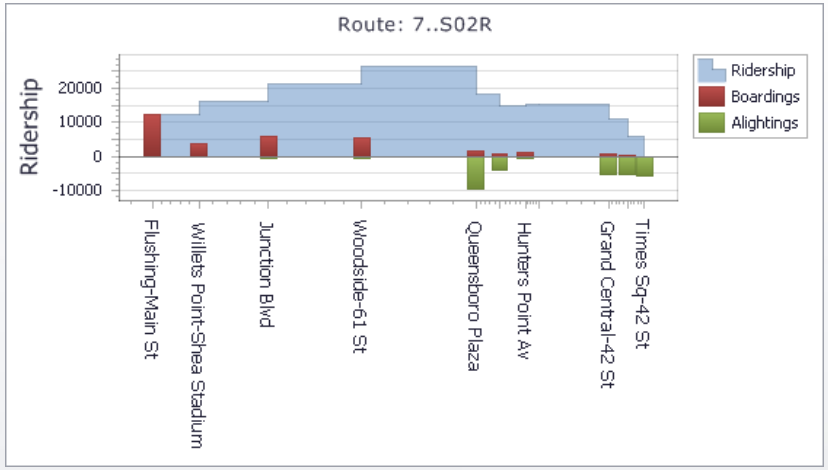


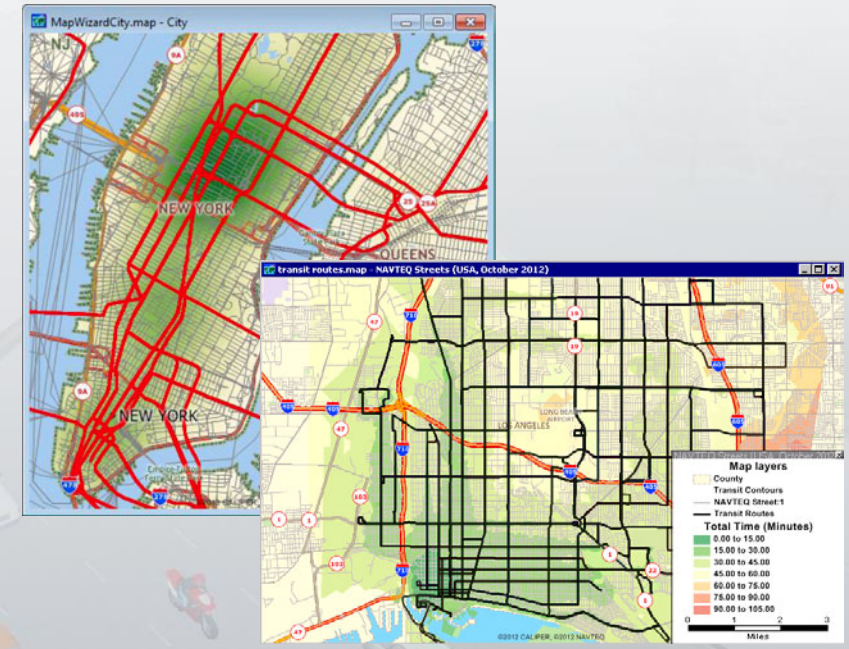


- Activity Based Modelling

Transit Enhancements

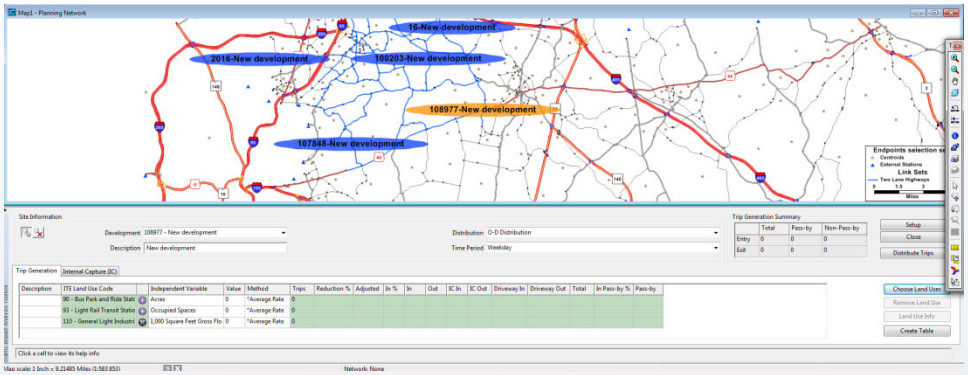
- Transit schedule handling
- Schedule-based skimming & assignment
- Enhanced route editor
- Multi-class, equilibrium pathfinder assignment
- Path-size logit route choice
- Refined accessibility calculator
- GTFS Import and Export
- Enhanced reports and graphics

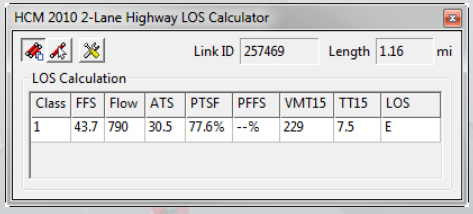




Major New Functionality

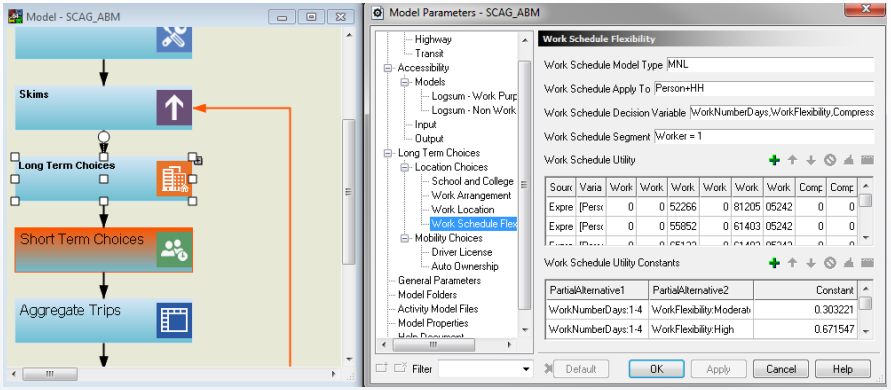
- Activity Model Platform and Interface Support
- Comprehensive traffic impact tools
- Accessibility calculators for all modes
- Nested logit estimation improvements and support for weights
- Enhancements for HERE (formerly NAVTEQ) networks and HERE Traffic data
- Key HCM 2010 LOS calculations
- MOVES
- Dynamic Multi-day Rail Waybill Assignment



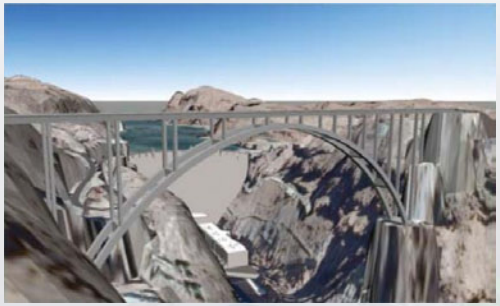


New Interface and GIS Features

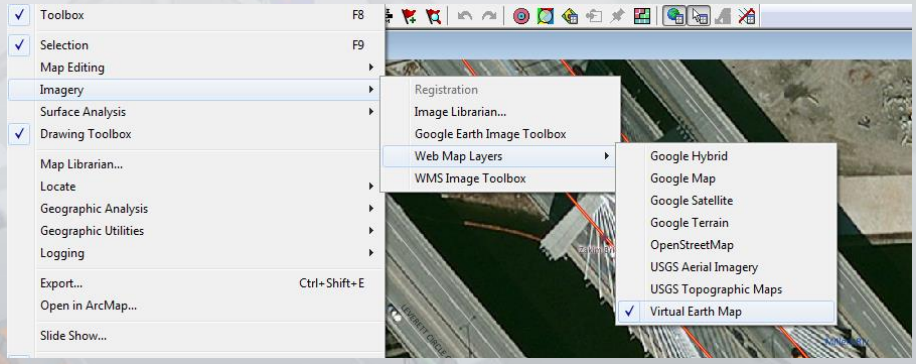
- Flowchart and parameter editor enhancements
- GISDK Support for object-oriented programming, classes, and methods



- 3D support for VRML, Sketchup, Autodesk 3D



- Web map layers including Google, OpenStreets, & Virtual Earth
- New Data

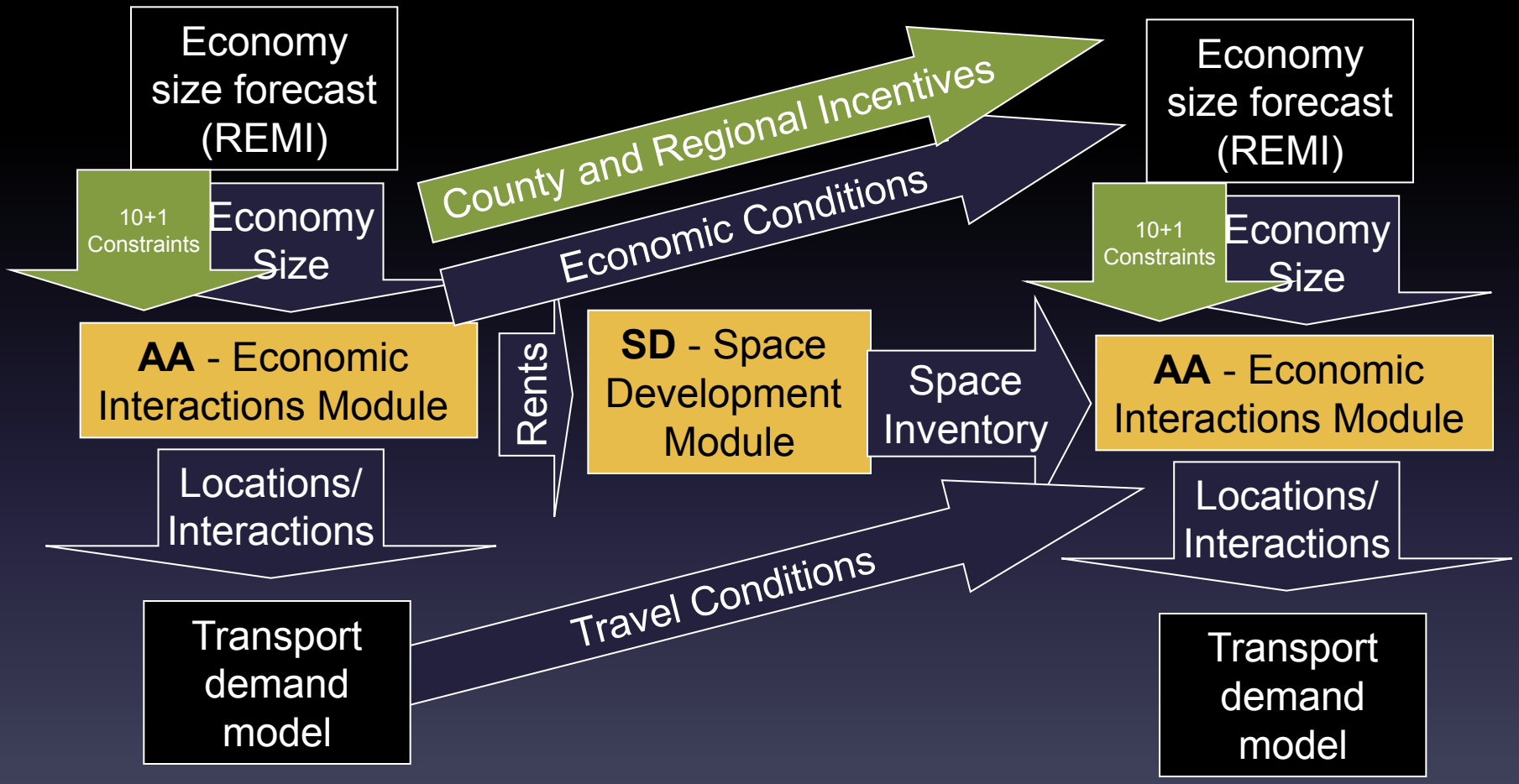


[15]

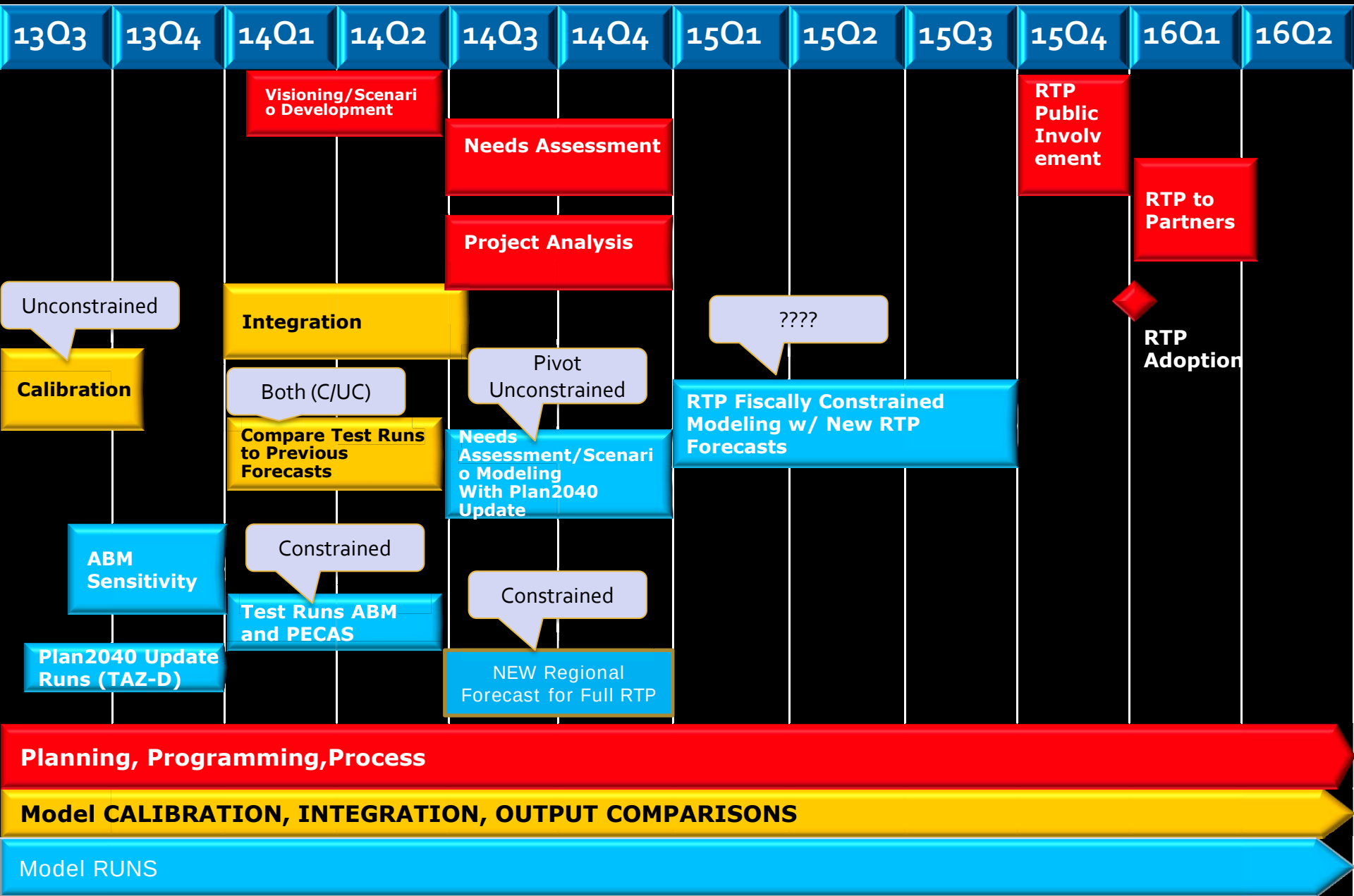
RTP forecasting with the Atlanta PECAS land use model

John E. Abraham
HBA Specto

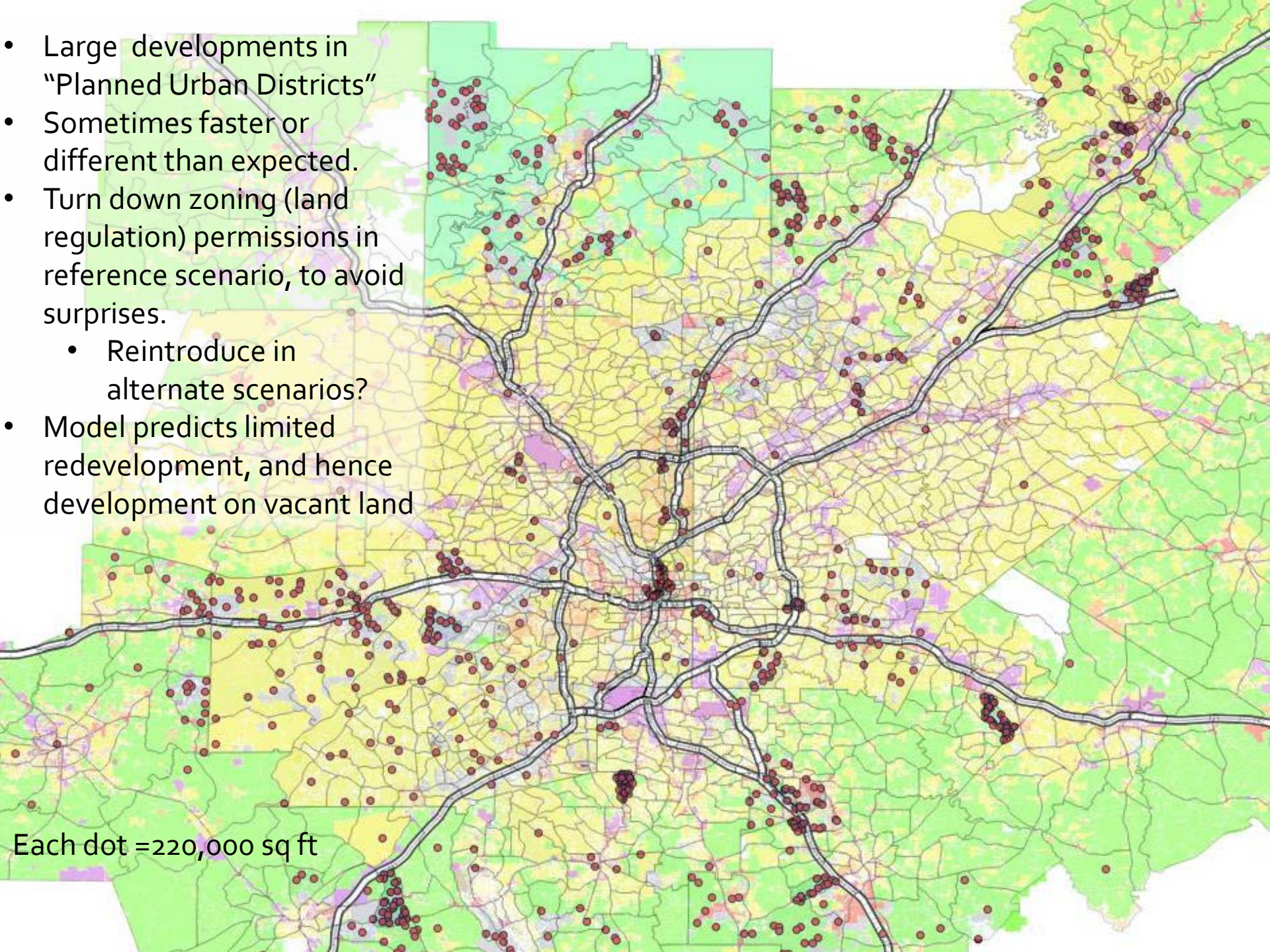
PECAS


Economy size forecast (REMI)
10+1 Constraints
Economy Size
County and Regional Incentives
Economic Conditions
Economy size forecast (REMI)
10+1 Constraints
Economy Size
AA - Economic Interactions Module
Rents
SD - Space Development Module
Space Inventory
AA - Economic Interactions Module
Locations/ Interactions
Locations/ Interactions
Travel Conditions
Transport demand model
Transport demand model
Time t
Time t + 1

RTP PRocess


13Q3
13Q4
14Q1
14Q2
14Q3
14Q4
15Q1
15Q2
15Q3
15Q4
16Q1
16Q2
Visioning/Scenario Development
Needs Assessment
Project Analysis
RTP Public Involvement
RTP to Partners
RTP Adoption
Unconstrained
Calibration
Integration
Both (C/UC)
Compare Test Runs to Previous Forecasts
????
RTP Fiscally Constrained Modeling w/ New RTP Forecasts
Pivot Unconstrained
Needs Assessment/Scenario Modeling With Plan2040 Update
ABM Sensitivity
Constrained
Test Runs ABM and PECAS
Constrained
NEW Regional Forecast for Full RTP
Plan2040 Update Runs (TAZ-D)
Planning, Programming,Process
Model CALIBRATION, INTEGRATION, OUTPUT COMPARISONS
Model RUNS

- Large developments in "Planned Urban Districts"
- Sometimes faster or different than expected.
- Turn down zoning (land regulation) permissions in reference scenario, to avoid surprises.
  - Reintroduce in alternate scenarios?
- Model predicts limited redevelopment, and hence development on vacant land



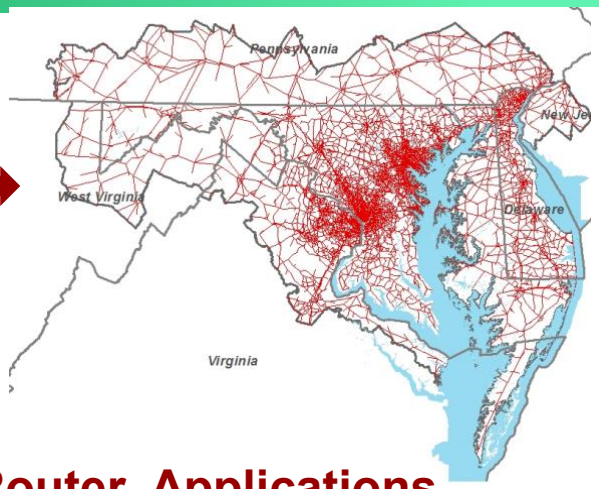
[16]

Large-scale dynamic traffic routing for statewide transportation planning

Sevgi Erdogan
University of Maryland

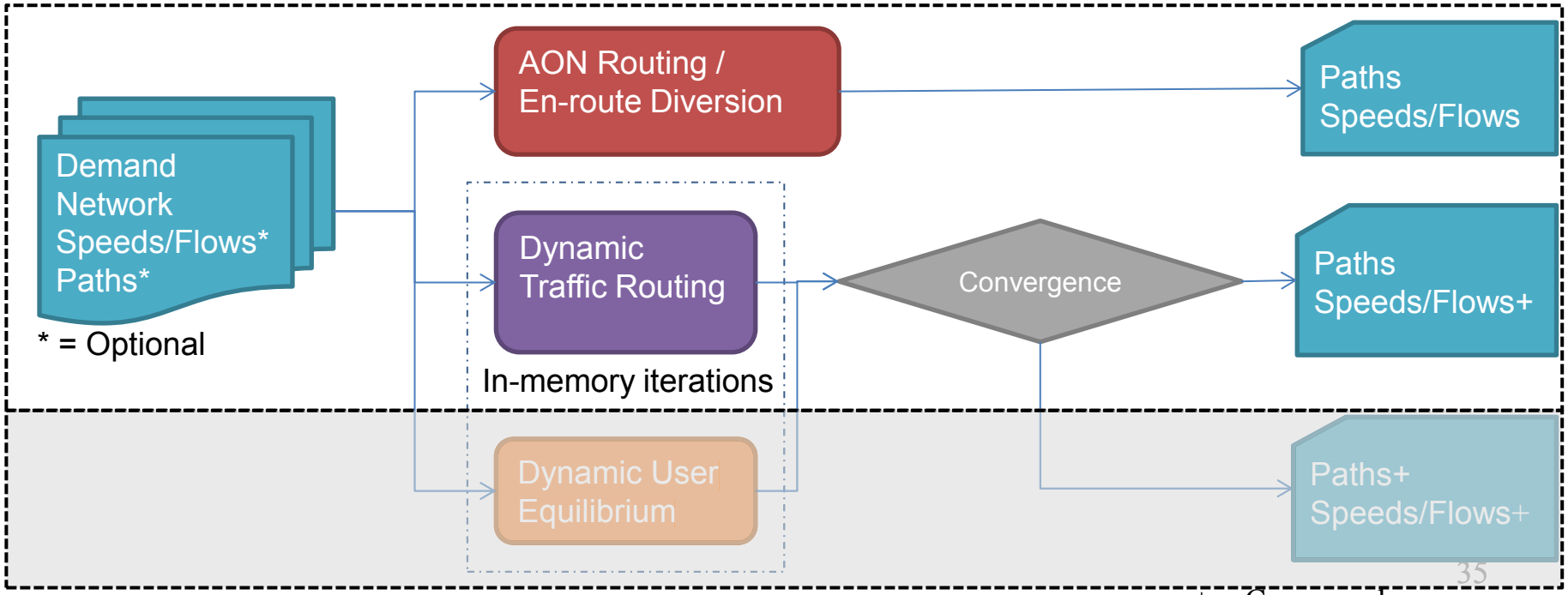
Methodology- Analytical DTA

Level 1
Nationwide
68,243 Nodes
87,785 Links
1,739 Zones



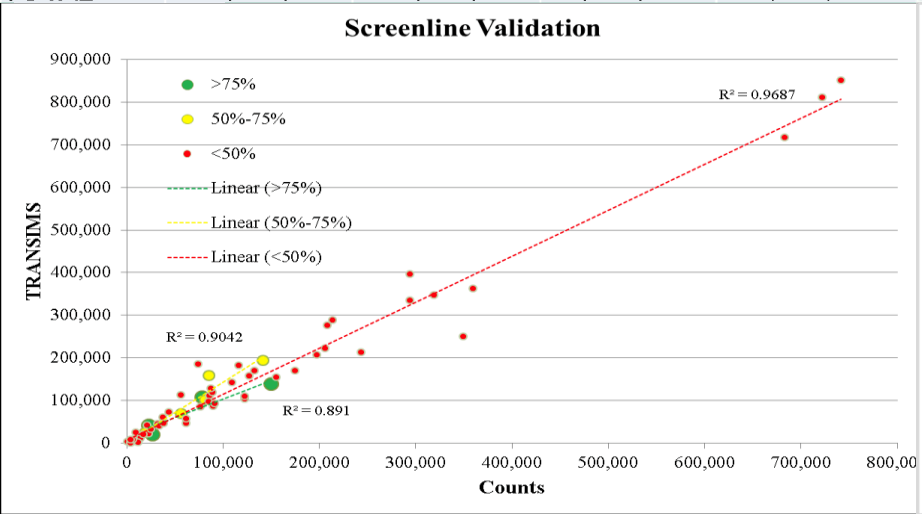
Level 2
Statewide
21,748 Nodes
31,116 Links
1,811 Zones

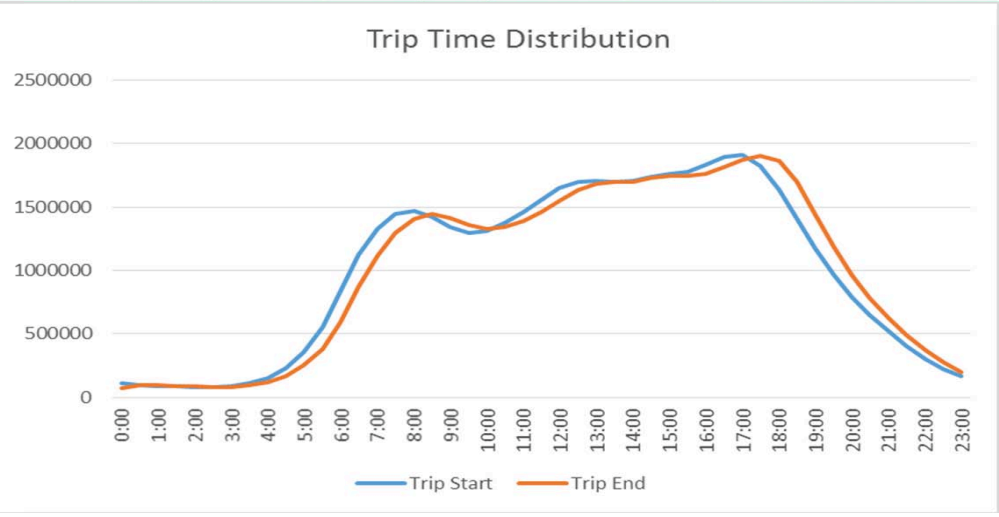
TRANSIMS Version 6 Router Applications

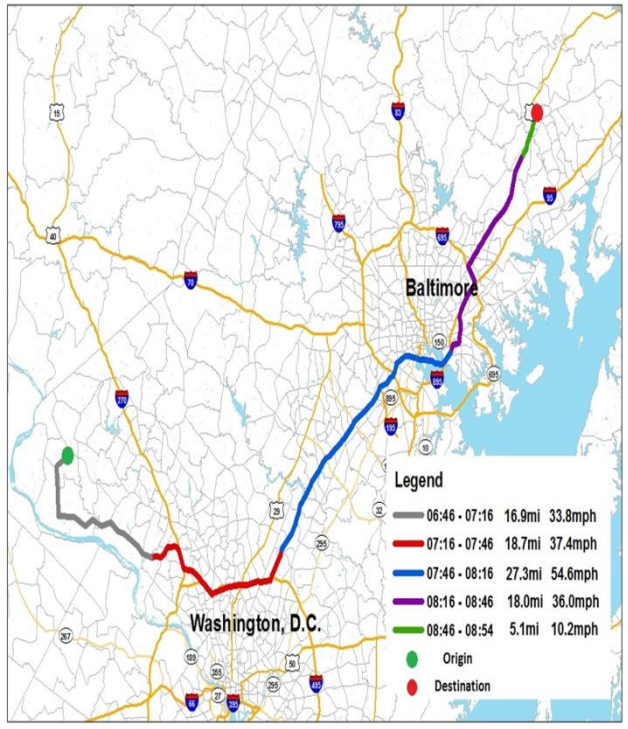


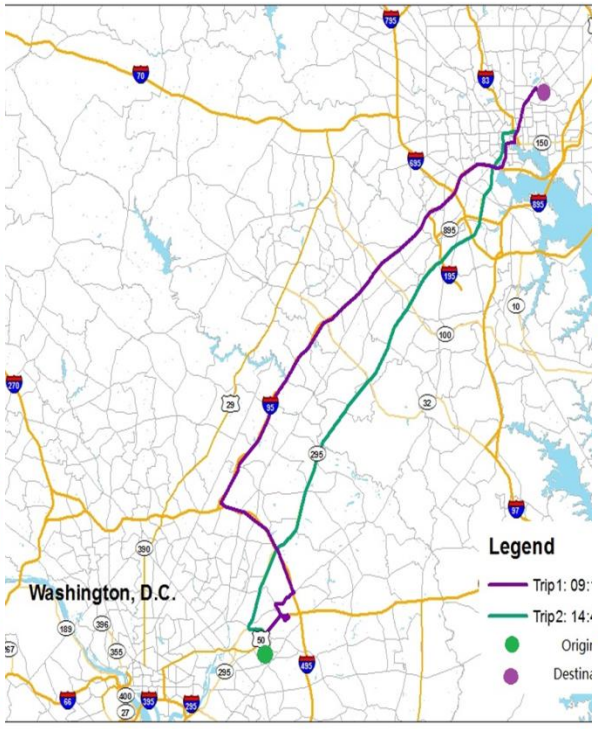
	VMT (vehicle miles traveled)		VHT (vehicle hours traveled)	
	TRANSIMS	MSTM	TRANSIMS	MSTM
TOTAL	172,944,424	149,251,620	5,137,976	5,045,544

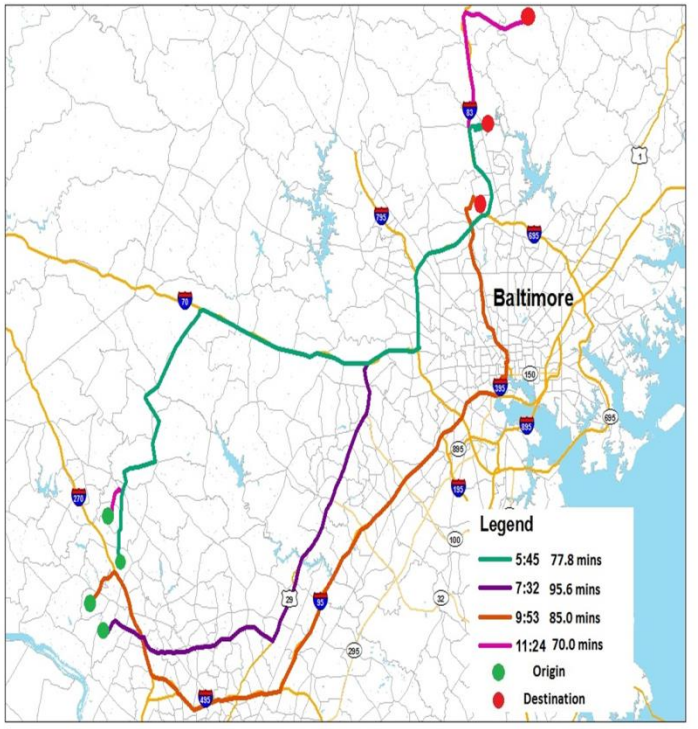
	Trips Started	Trips Completed	Spillover	%Spillover
AM	3,985,413	3,601,209	676,889	~17.0
PM	5,498,286	5,459,362	859,670	~15.6







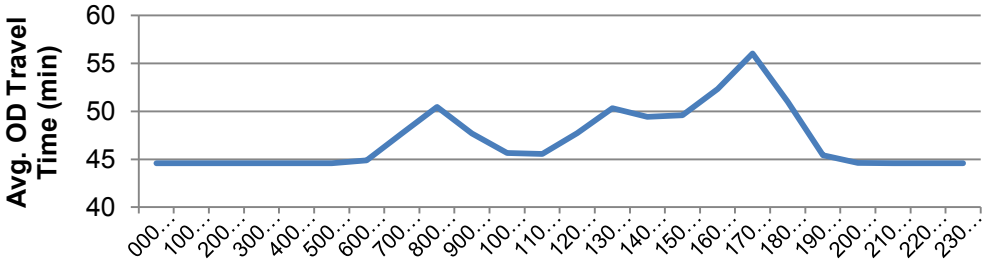


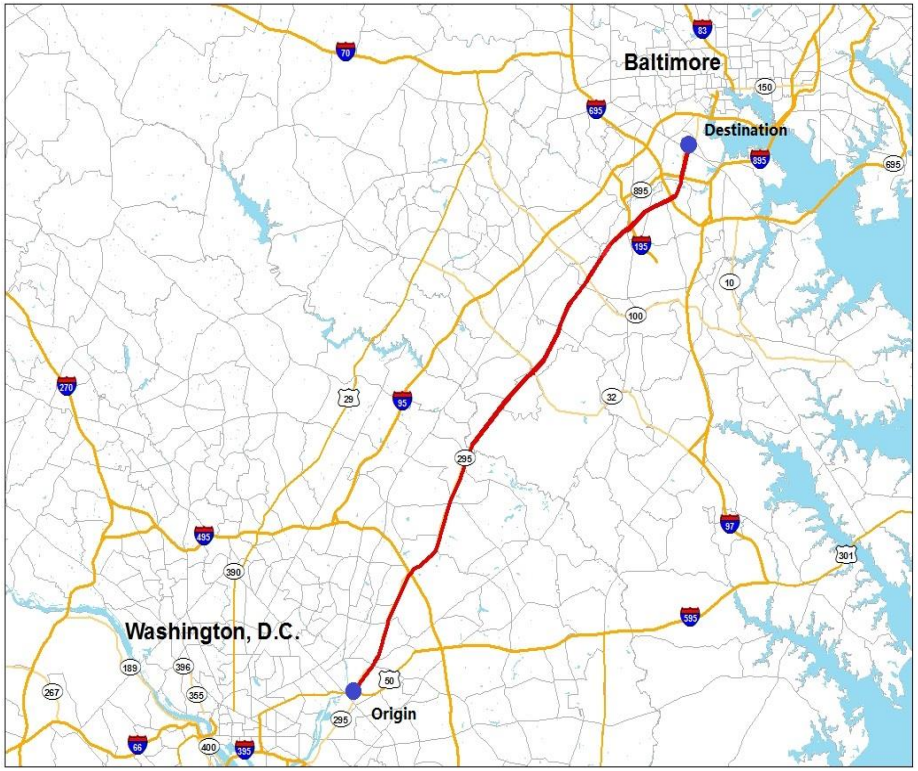


Time-Dependent Performance Measures

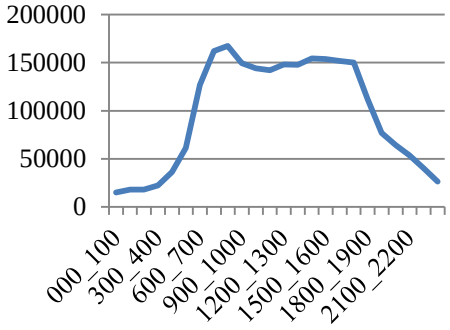
Congested Segment

Change in Average Travel Time by Departure Time

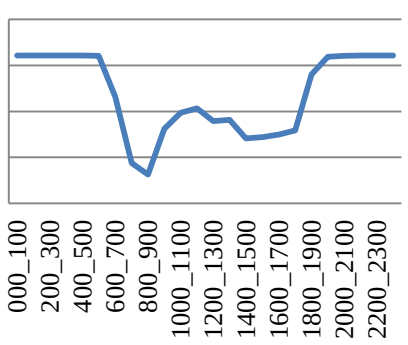




Volume by TOD



Average Speed by TOD



Remarks

Benefits

- Continuous day representation
- Higher time resolution
- Tracking individual travelers
- Scenario analysis

Challenges

- Level of detail in network and demand representation
  - →implications on run and processing times
  - →implications on software and hardware
- Visualization

Next Steps

- Further validation
- Integrating it with MSTM