Comprehensive Bicycle Volume Estimation from Sparse Data

C Alec Gosse Phd
alec.gosse@ccri.com
(434) 284-9432

DATA TO KNOWLEDGE

Bike Data is hard to come by

- State DOTs generally don't count bicycles as they do motorized traffic
- Specialized hardware is needed for automated counts
- Manual counting is labor-intensive
- Bicycle usage is more variable than motorized traffic
    - even more data are necessary to capture underlying parameters

agencies with limited..

- budgets for bicycle data collection
- some existing bicycle-specific modeling
- can collect modest amounts of counts
- may not be able to get meaningful outputs

Leverage existing data and look for additional sources

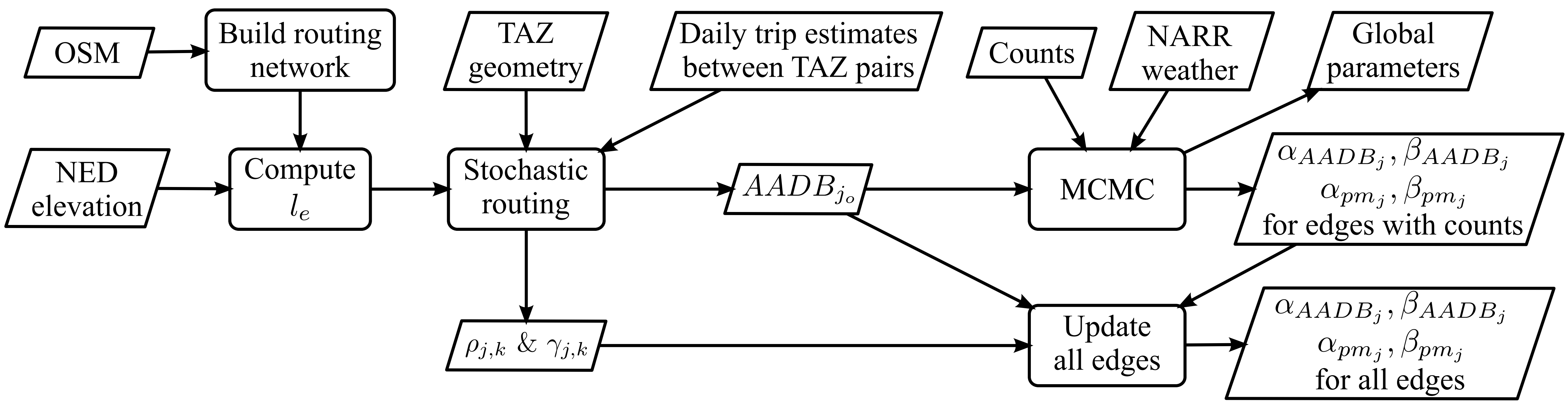
A Volume Model to Combine available data

- Manual intersection counts
- Short duration automated counts
- Continuous count stations
- Route prediction algorithms
    - GPS studies
    - topography
- Likely commute patterns
- Weather histories

The Concept

- Temporal Factoring - we generally don’t have continuous year-round data
- Spatial Factoring - we can’t observe every street and path
- Network-wide analyses for safety and planning purposes thanks to spatially and temporally continuous synthetic data

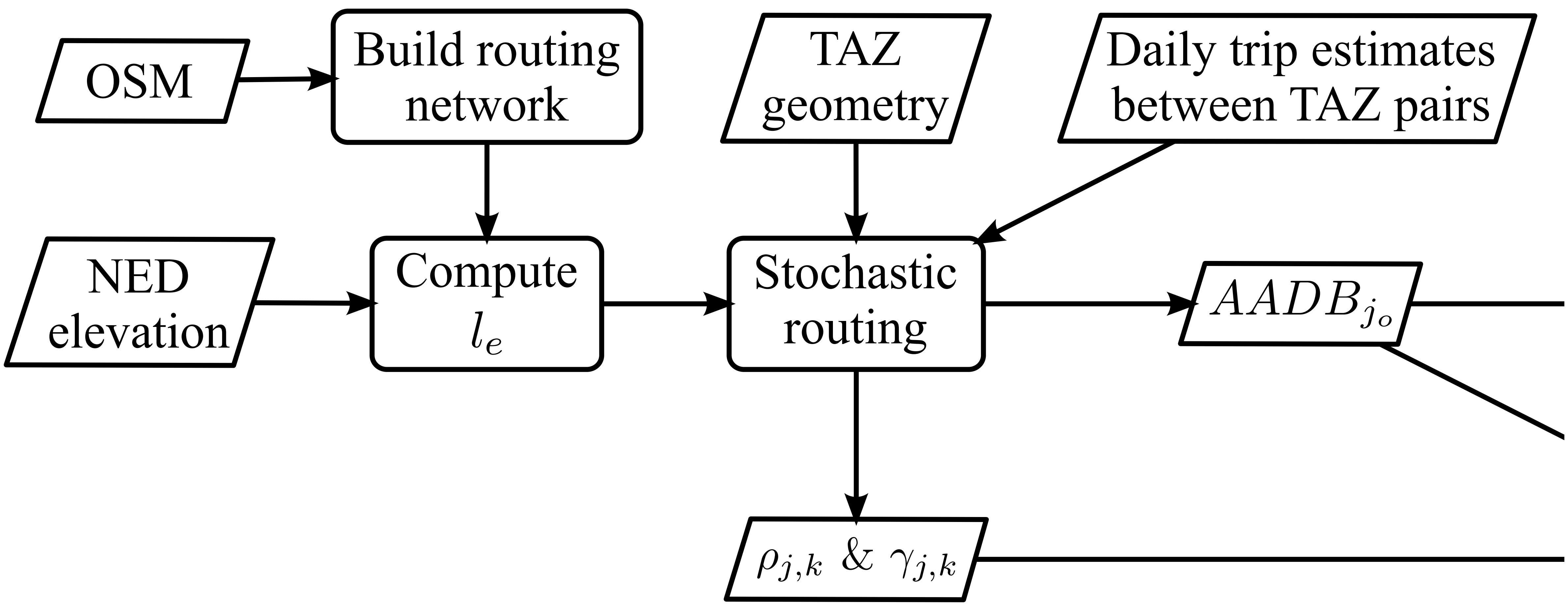
Information flow



Routing

- Generalized least cost routing
  - instantaneous slope (National Elevation Data Set)
  - presence of dedicated bicycle facilities (from Open Street Map)
  - motorized AADT
  - distance
- Stochastic routing between pairs of TAZs
  - more trips for closer TAZs since origin and destination are random
  - weights of each cost function randomly varied each run to yield a realistic diversity of routes

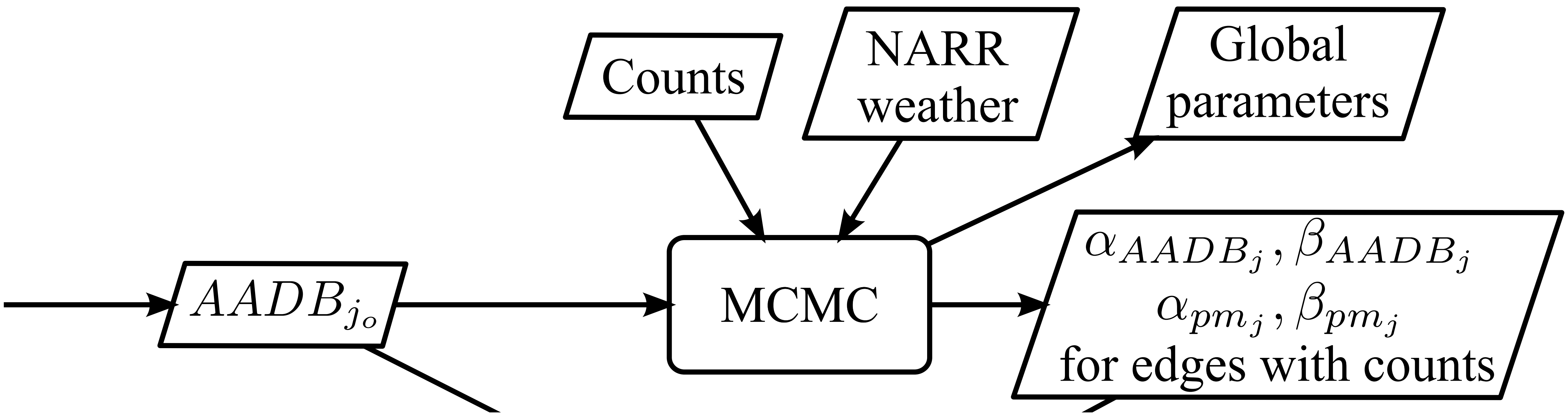
Information flow - Routing



Temporal Factoring

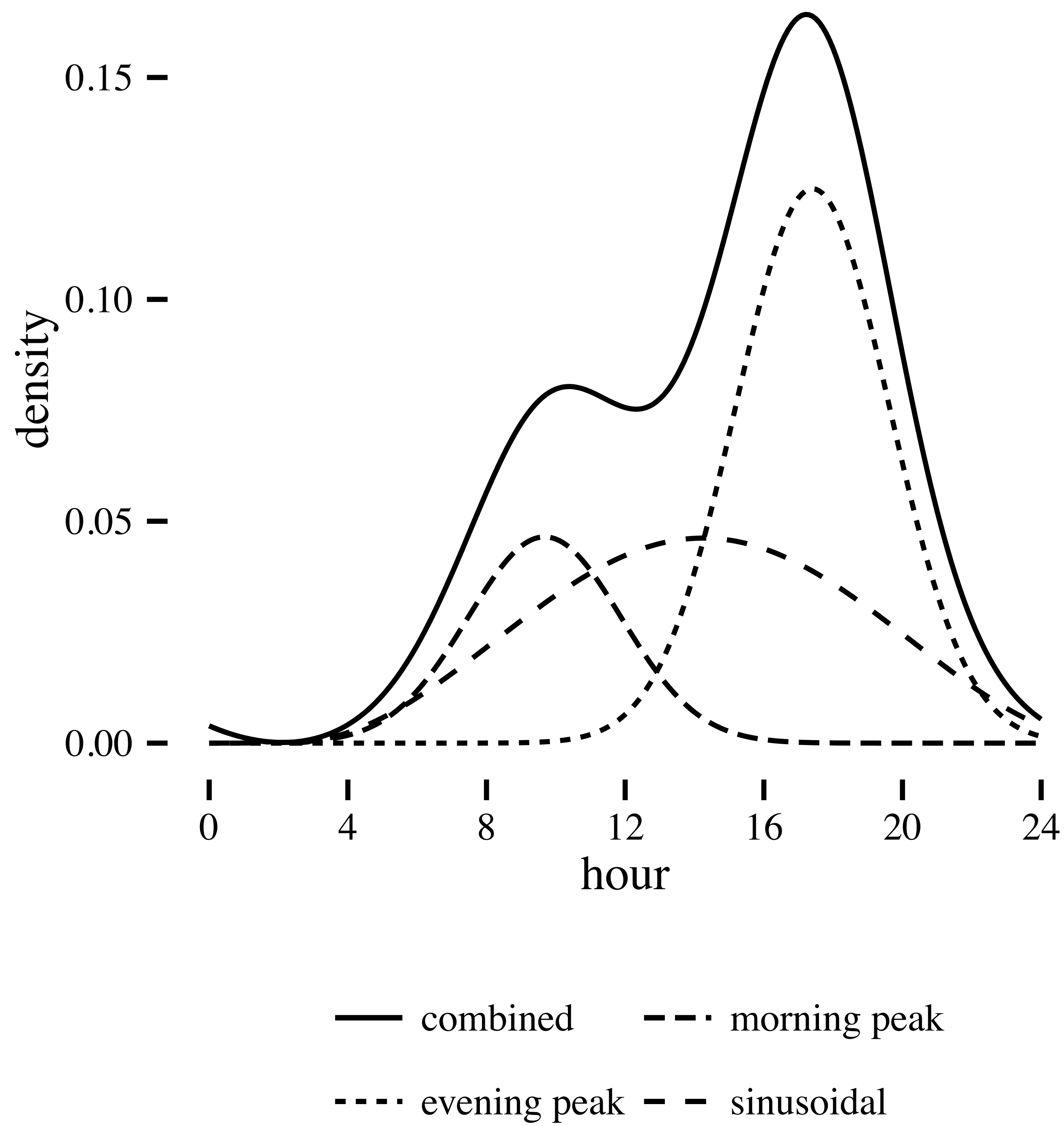
- Hourly variation
  - sinusoidal base demand curve
  - morning and evening gaussian peaks
- Weekday vs. Weekend
- Temperature and Precipitation
- Markov-Chain Monte Carlo sampling of posterior parameter distributions
  - fit to gamma or beta distributions as appropriate

Information flow - Temporal Factoring

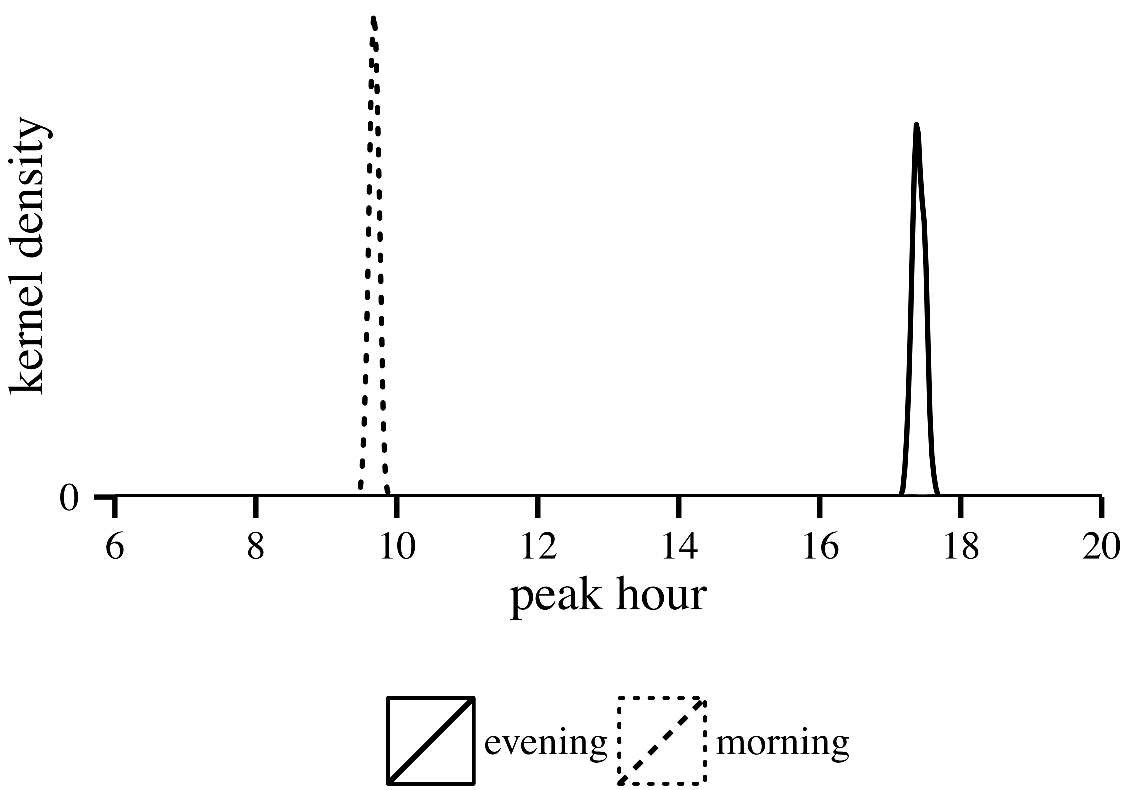


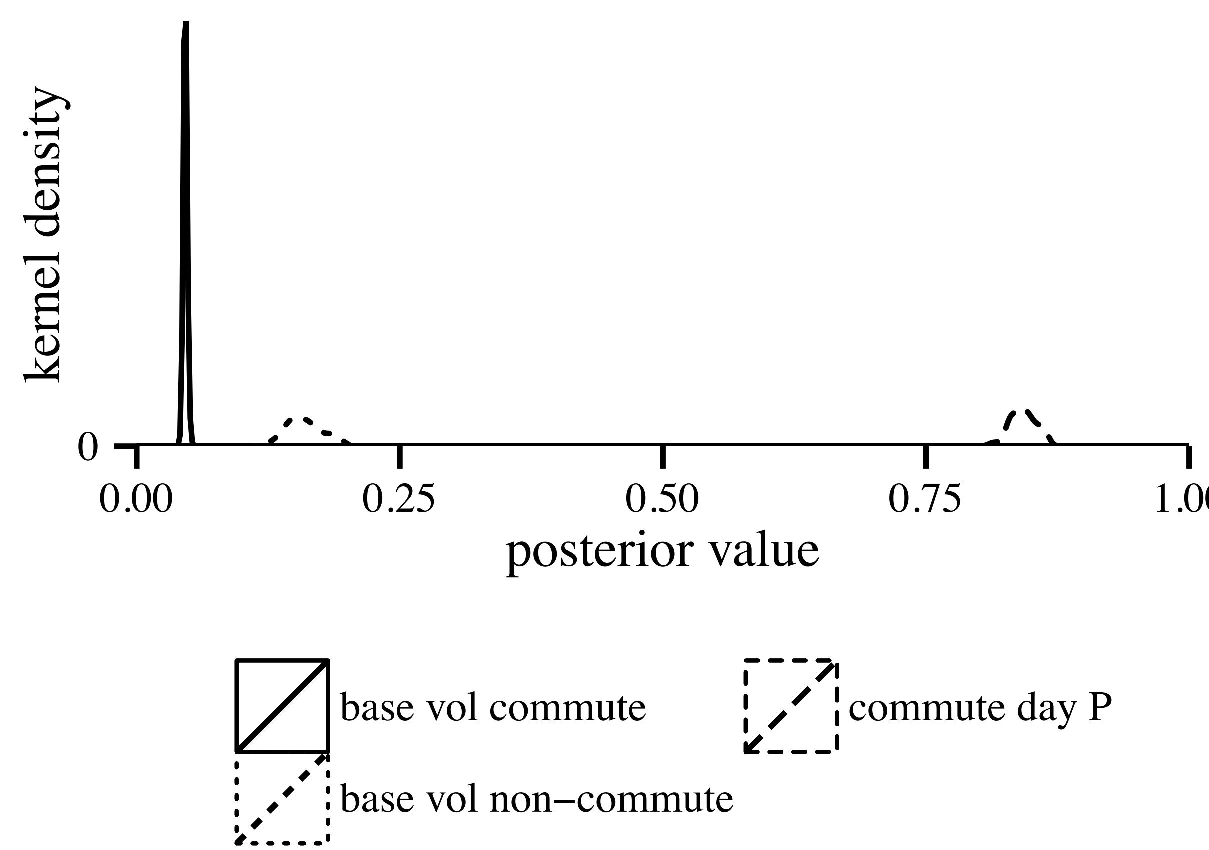
$$\mu_i = AADB_{j(i)} F_{p_i} F_{t_i} F_{c_i} F_{h_i}$$

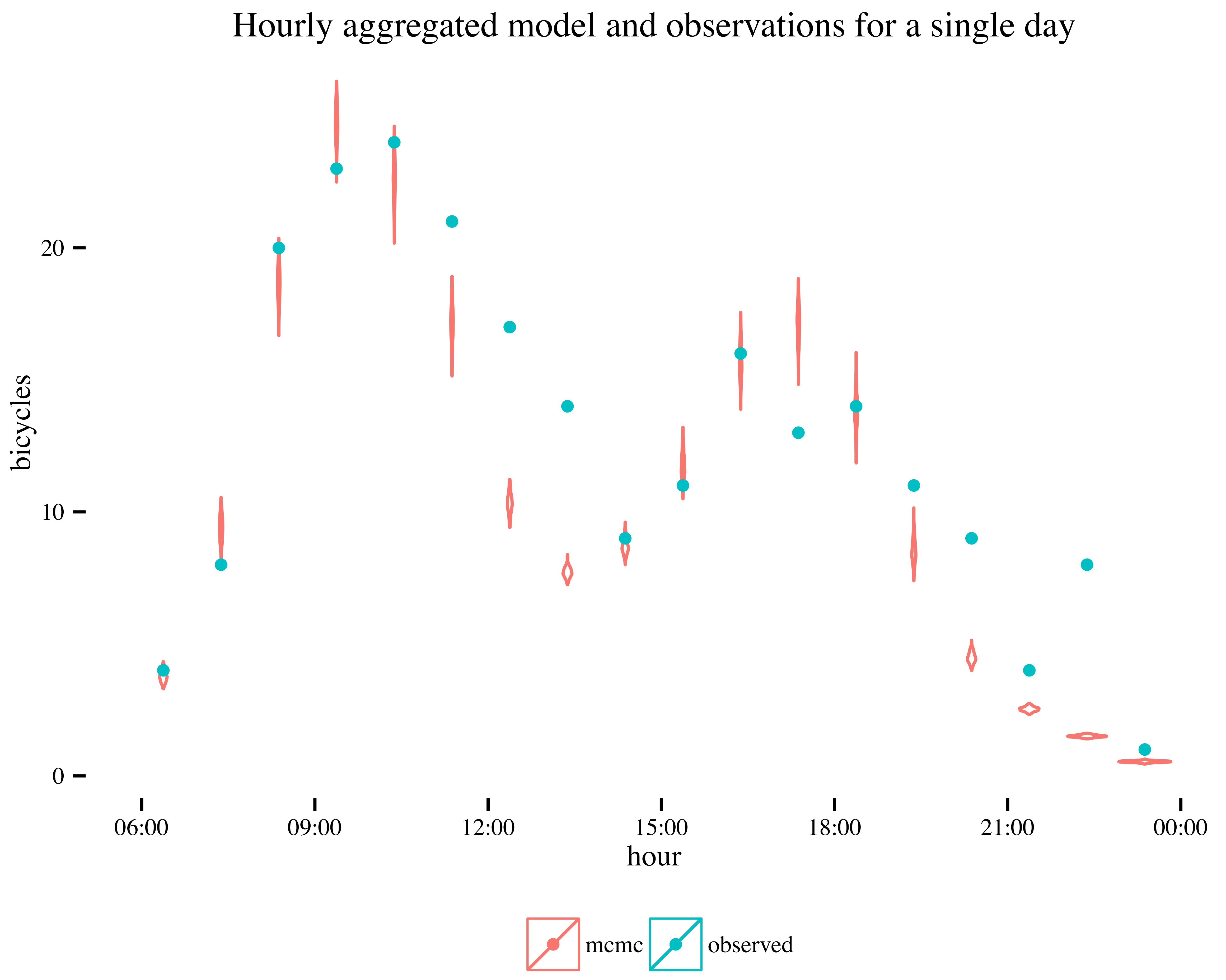
Hourly variation



Hourly variation



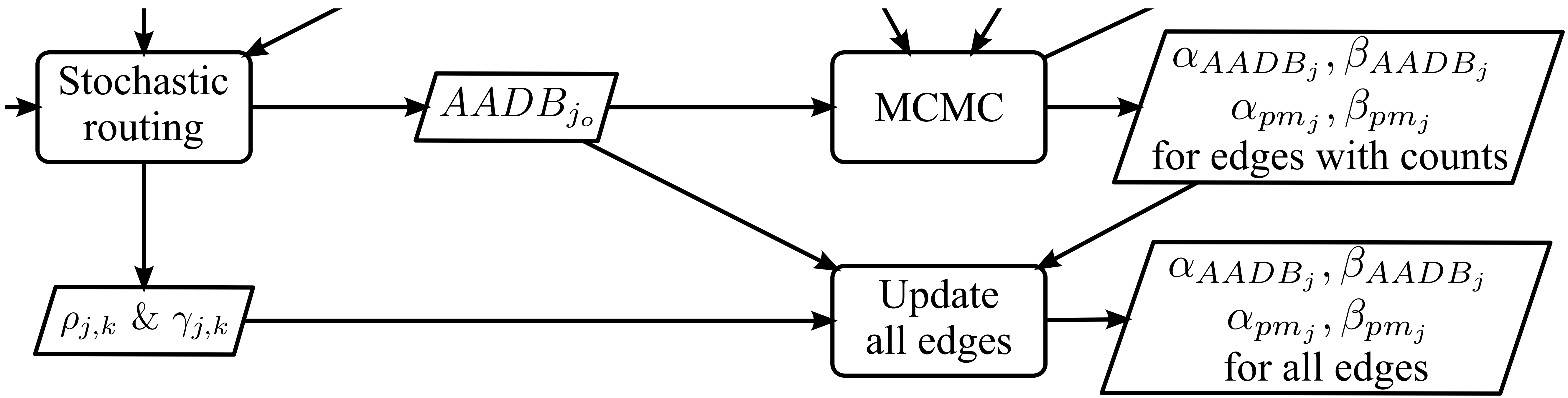


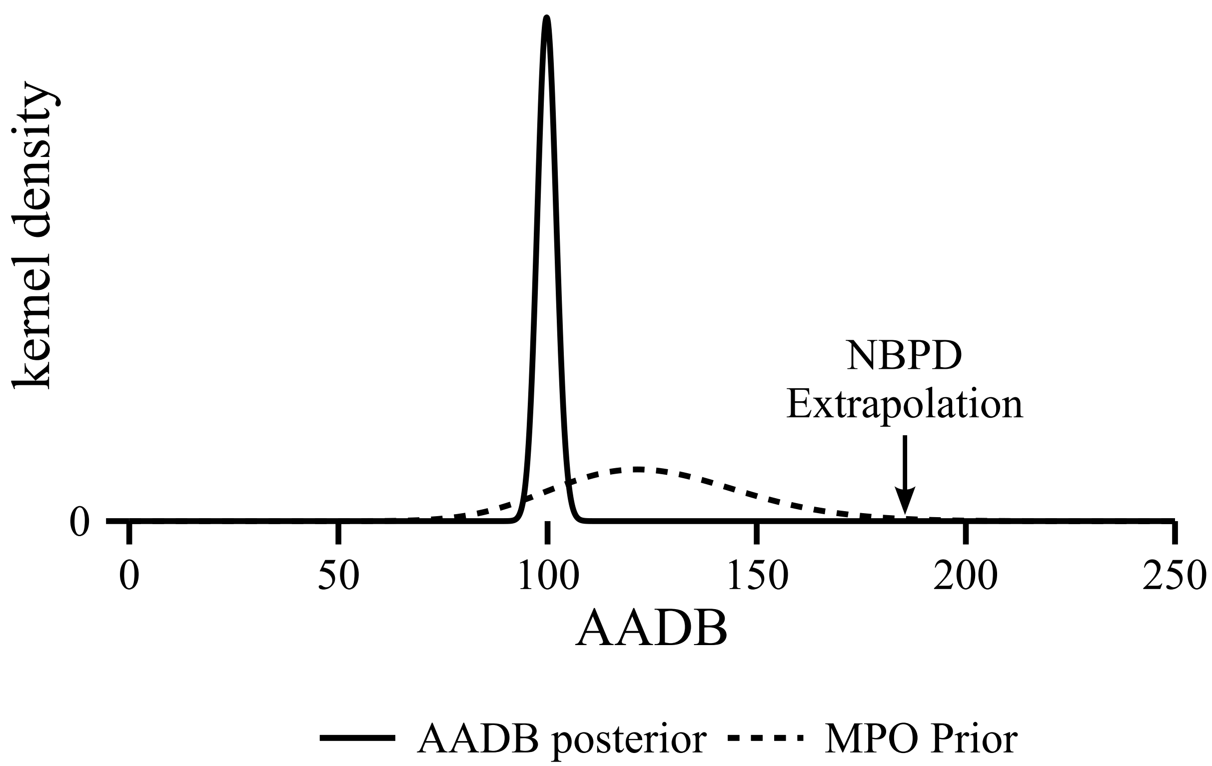

Hourly aggregated model and observations for a single day
bicycles
20
10
0
06:00
09:00
12:00
15:00
18:00
21:00
00:00
hour
mcmc
observed

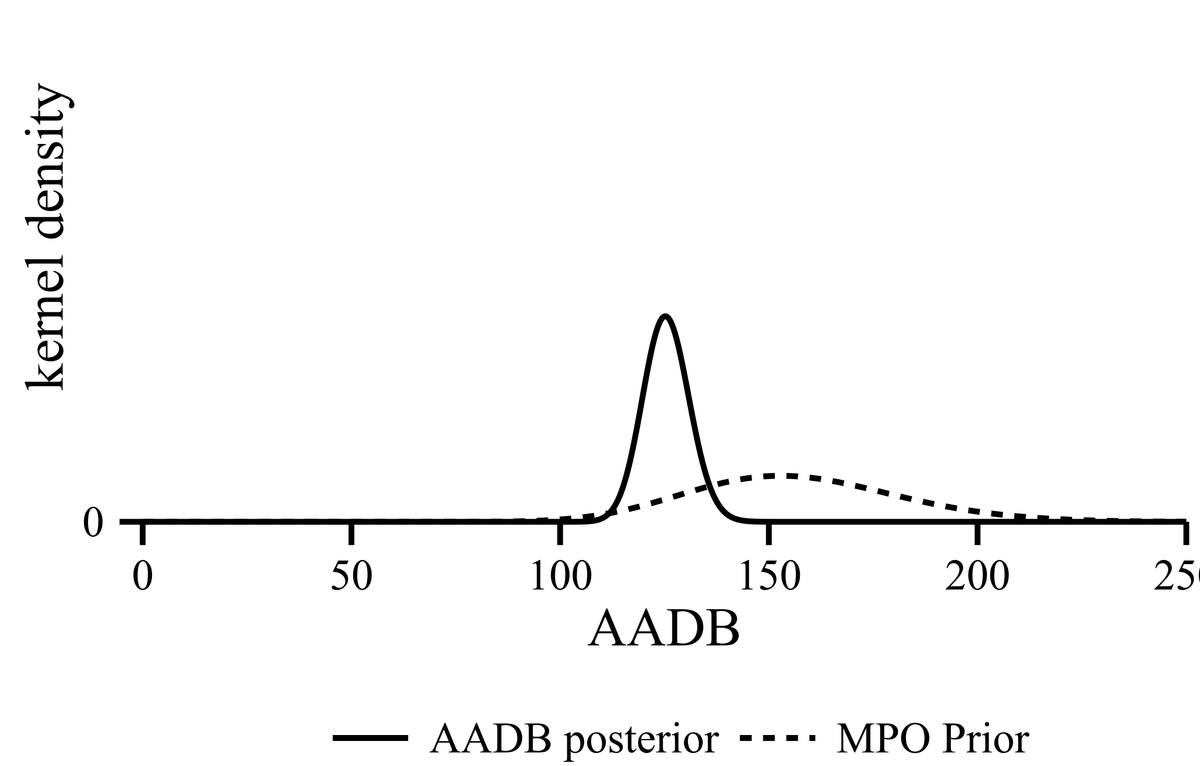
Spatial Factoring

- Expected bicycle usage on unobserved streets
- Correlations and volume ratios between all related pairs of directional streets are computed from the stochastic routes
- Bayesian updating of prior AADB estimates
  - using posterior AADB from temporal factoring modified by correlation and expected volume ratio
- Results are posterior distributions for AADB and morning peak proportion for every street

Information flow - Spatial Factoring




kernel density
NBPD
Extrapolation
0
0
50
100
150
200
250
AADB
AADB posterior
MPO Prior


kernel density
0
0
50
100
150
200
250
AADB
AADB posterior
MPO Prior


Ivy Road
Count
Location
Rugby Road
Correlated
Location

AADB (both directions)
10–50
50–100
100–200
200–300
>300
Hours of Counts
0.5 - 200
>200
Variance
Low
High
Hydraulic Road
Seminole Trail
Emmet Street North
Barracks Road
Emmet Street South
Rugby Road
Grady Avenue
10th Street Northwest
Preston Avenue
McIntire Road
University Avenue
McCormick Road
Alderman Road
Jefferson Park Avenue
West Main Street
Ridge Street
High Street East
Market Street East

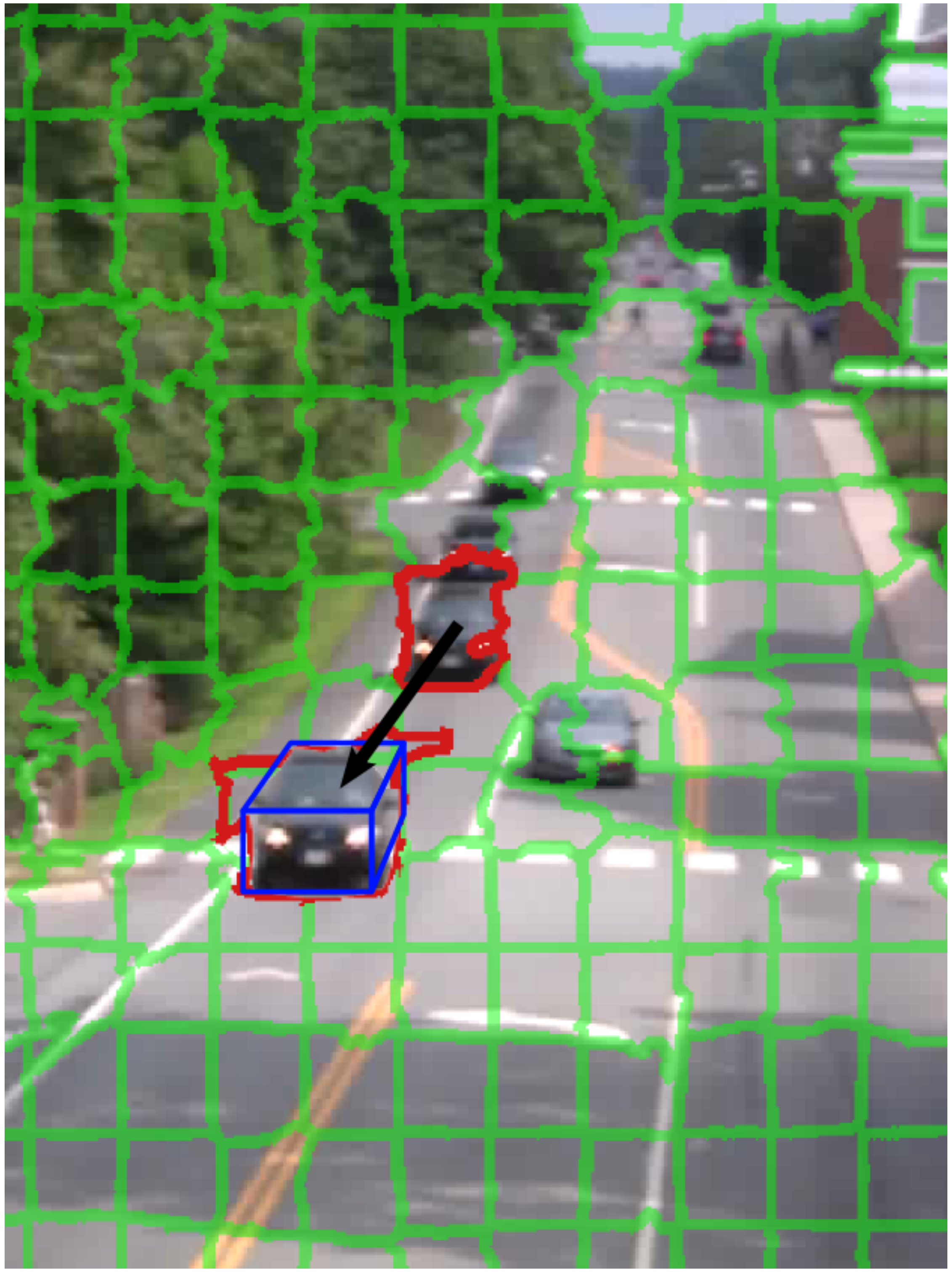
With these data

- Immediate visualization and planning
    - Evaluating current impacts of proposed infrastructure
- Feedback loops with Travel Demand Model
- Network-wide exposure values for safety prioritization
- Future scenario modeling using latent growth term(s)

Automated counts from traffic signal cameras

Vehicle tracking

- In-between complexity
  - simple presence detection
  - advanced real-time tracking
- super-pixel method to identify vehicles
- bounding box for classification and recognition in departing view
- speed and trajectory



Thank you | Questions?

alec.gosse@ccri.com