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Adding temporal information to direct-demand models: Hourly estimation of bicycle and pedestrian traffic in Blacksburg, VA

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ABSTRACT

Cycling and walking are environmentally-friendly transport modes, providing alternatives to automobility. However, exposure to hazards (e.g., crashes) may influence the choice to walk or cycle for risk-averse populations, minimizing non-motorized travel as an alternative to driving. Most models to estimate non-motorized traffic volumes (and subsequently hazard exposure) are based on specific time periods (e.g., peak-hour) or long-term averages (e.g., Annual Average Daily Traffic), which do not allow for estimating hazard exposure by time of day. We calculated Annual Average Hourly Traffic estimates of bicycles and pedestrians from a comprehensive traffic monitoring campaign in a small university town (Blacksburg, VA) to develop hourly direct-demand models that account for both spatial (e.g., land use, transportation) and temporal (i.e., time of day) factors. We developed two types of models: (1) hour-specific models (i.e., one model for each hour of the day) and (2) a single spatiotemporal model that directly incorporates temporal variables. Our model results were reasonable (adj-R^2 for the hour-specific [spatiotemporal] bicycle model: ~0.47 [0.49]; pedestrian model: ~0.69 [0.72]). We found correlation among non-motorized traffic, land use (e.g., population density), and transportation (e.g., on-street facility) variables. Temporal variables had a similar magnitude of correlation as the spatial variables. We produced spatial estimates that vary by time of day to illustrate spatiotemporal traffic patterns for the entire network. Our temporally-resolved models could be used to assess exposure to hazards (e.g. air pollution, crashes) or locate safety-related infrastructure (e.g., striping, lights) based on targeted time periods (e.g., peak-hour, nighttime) that temporally averaged estimates cannot.

1. Introduction and literature review

Non-motorized (i.e., bicycle and pedestrian) transportation has experienced growing support from local government, public health officials, as well as transportation and environmental organizations (Pucher & Buehler, 2010; Gärling & Ettema, 2014; Geller, 2003; Sallis et al., 2006). This support is due in part to walking and cycling's role in environmentally-sustainable transportation, providing alternatives to the car for many trips, particularly when integrated with public transit (Ogilvie et al., 2004; Scheepers et al., 2014; Nieuwenhuijsen and Khreis, 2016; Buehler and Pucher, 2012). This trend has motivated planners to encourage risk-averse populations to participate in non-motorized travel (TRB, 2005), which highlights the need for studies on traffic-related exposure assessment (Bigazzi & Figliozzi, 2014; Vanparijs et al., 2015). In previous efforts, exposure assessment has typically characterized

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long-term average (e.g., annual) estimates of both the population (e.g., cyclists and pedestrians) and the exposure (e.g., accidents, air toxics) (Raford & Ragland, 2005); however, exposure to hazards may vary by time of day (Hatzopoulou et al., 2013; Jerrett et al., 2005).

Developing models that are capable of estimating temporally-resolved bicycle and pedestrian traffic volumes at locations without traffic counts may improve exposure assessment. For example, intersection or block-level bicycle counts enable the comparison of spatial patterns between bicycle traffic and ambient air pollution concentrations (Strauss et al., 2012; Hankey et al., 2017a). Similarly, crash analyses could be reported as a function of hourly volumes instead of annual average volumes (Rothenberg et al., 2016; Murphy et al., 2017) since risk factors for crashes may change during nighttime hours (Johnson et al., 2015). In general, aggregated exposure measures (e.g., Annual Average Daily Traffic [AADT]) may fail to capture the exposure variability by time of day suggesting a need for temporally resolved traffic volumes (e.g., hourly traffic) as an input for exposure assessment studies (Ivan et al., 2000; Qin et al., 2006).

The US Federal Highway Administration (FWHA) has recently synthesized existing methods for estimating bicycle and pedestrian exposure to risk (FWHA, 2017). Models of bicycle and pedestrian volumes include linear regression (Jones et al., 2010; Lindsey et al., 2006; Schneider et al., 2009b), Poisson or negative binomial regression (Wang et al., 2014; Merom et al., 2003), generalized linear mixed models (Chen et al., 2017) or geographically weighted regression (Yang et al., 2017) indicating that there is not consensus on a single modeling approach. Typically, non-motorized traffic modeling efforts estimate either daily averages or peak hours (Fagnant & Kockelman, 2016; Figliozzi et al., 2014; Murphy et al., 2017; Schmiedeskamp & Zhao, 2016; Tabeshian & Kattan, 2014; Jones et al., 2010; Hankey & Lindsey, 2016; Hankey et al., 2017b; Yang et al., 2017). Direct-demand models are a potentially useful modeling approach that employ a wide range of predictor variables including: transportation, land use, economic factors, and weather conditions (Griswold et al., 2011; Molino et al., 2009; Radwan et al., 2016; Miranda-Moreno & Fernandes, 2011; Pulugurtha & Repaka, 2008; Schneider et al., 2009a, 2009b; Wang et al., 2016). However, the outputs (and resulting estimates of spatial patterns of non-motorized traffic) from previous direct-demand models usually do not incorporate temporal variability directly in the modeling approach. Developing models for singular time periods (e.g., peak hours) could potentially hinder efforts to conduct exposure assessment on a more temporally-refined basis. For example, estimates of off-peak hours would be useful for non-motorized transportation studies on crime risk or activity patterns at night (e.g., near entertainment districts). Other attempts to estimate hourly non-motorized traffic using adjustment factors often suffer from an incomplete network of continuous count data to properly develop factor groups (Gosse & Clarens, 2014; Hottenstein et al., 1997; Nordback & Sellinger, 2014; NCHRP, 2014).

In this paper, we use a dataset of automated non-motorized traffic counts to develop direct-demand models that are capable of hourly estimation of bicycle and pedestrian traffic volumes in Blacksburg, VA. We use model results to observe how spatial patterns of non-motorized traffic change by time of day and provide spatiotemporal, model-derived traffic estimates at all locations on the network. For example, we compare the fully normalized regression coefficients of commonly recognized land-use and transportation variables vs. temporal (i.e., time of day) variables on bicycle and pedestrian traffic volumes. The outputs of our models could be used to better assess exposure to hazards (e.g. air pollution, crashes) or safety-related infrastructure (e.g., striping, lights) for targeted time periods (e.g., peak-hour vs. nighttime) that temporally averaged estimates (e.g., daily averages) cannot.

2. Data and methods

We developed hourly direct-demand models of bicycle and pedestrian traffic based on count data from a non-motorized traffic monitoring campaign in Blacksburg, VA. The traffic monitoring data included hourly traffic counts of bicycles and pedestrians at 101 and 72 locations, respectively, for each mode. As explained below in Section 2.3.1, we annualized the hourly counts (by using reference sites to adjust short-duration counts) to obtain hourly traffic estimates for all 24 h of the day. Our modeling approach enabled us to explore differences in temporal and spatial patterns on an entire transportation network. Our overarching goal is to integrate temporal information into the direct-demand models and to provide time-specific traffic information for exposure and safety analyses.

2.1. Study location

Our study area is the small, rural college town of Blacksburg, VA (~42,000 total population including ~30,000 students; 50.2 km^2). Located in the New River Valley, the Town of Blacksburg is heavily influenced by Virginia Tech.

2.2. Site selection and data collection

We previously collected bicycle (pedestrian) counts at 101 (72) locations as part of a traffic monitoring campaign in 2015 (Fig. 1). The traffic monitoring campaign captured spatial variability by stratifying count locations by street functional class (e.g., major road vs. local road), centrality (a measure of bicycle trip potential called stress centrality as defined in McDaniel et al., 2014) and presence of facilities (e.g., bike lanes, sidewalks). Counts were recorded using automated counters to ensure 7 days of valid data at each location (we also deployed counters at four reference sites counting both bicycles and pedestrians continuously for the entire year). We aggregated the automated counts on an hourly basis at each location and annualized the hourly estimates using the reference site data. Further details (e.g., location type, estimation errors, and number of counts by location type) that describe the monitoring campaign can be found in Lu et al., (2017); further detail on annualizing the counts is introduced below in Section 2.3.1.

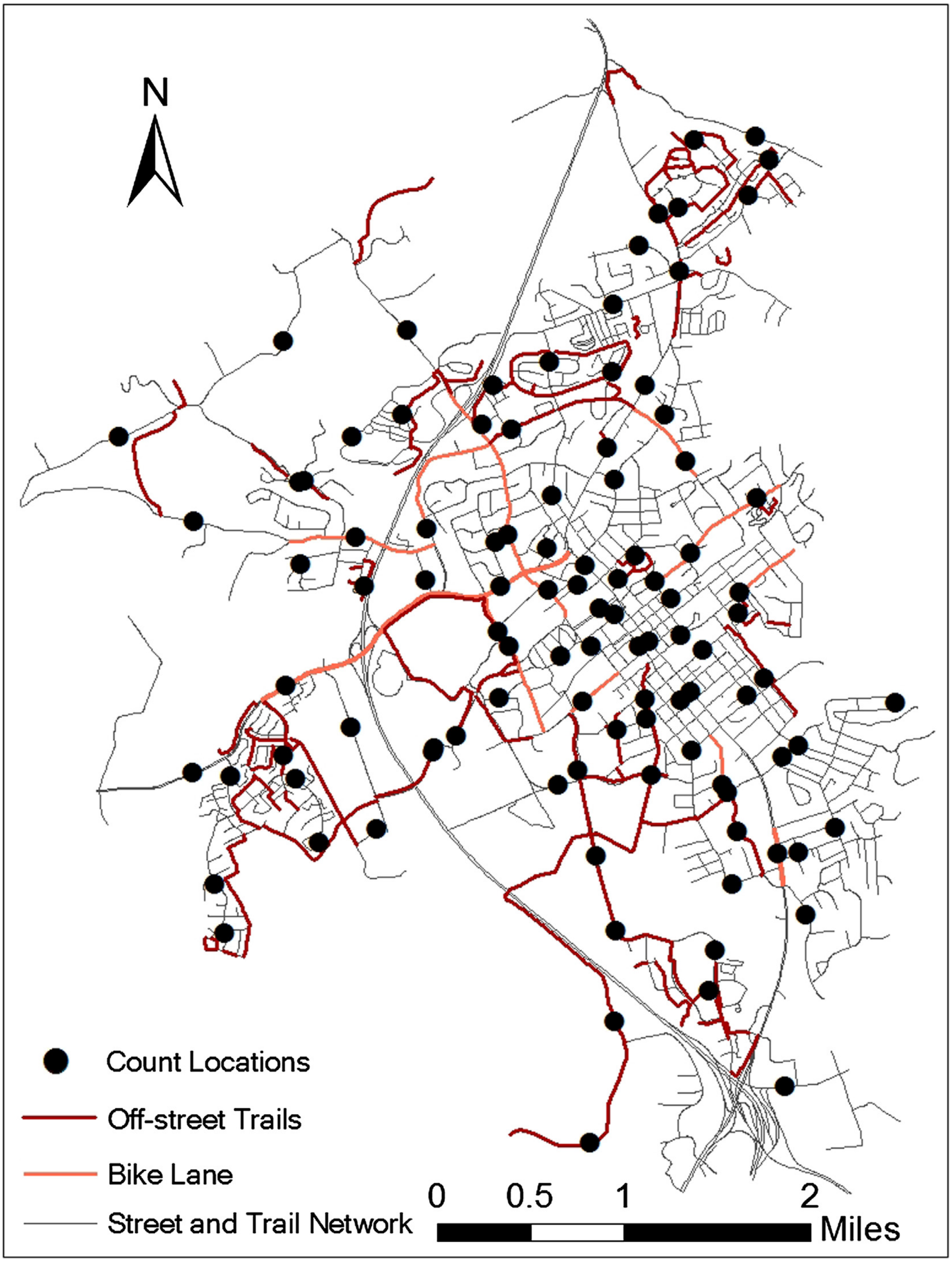

Fig. 1. Bicycle and pedestrian count locations in Blacksburg, VA.

2.3. Direct-demand models

Our direct-demand models were based on a stepwise regression approach that allows for varying buffer sizes of independent variables (e.g., land-use and transportation features). We developed two types of models to incorporate temporal variability during model-building: (1) twenty-four hour-specific models (i.e., one model for each hour of the day) and (2) a single spatiotemporal model that incorporates time of day as an additional predictor to the spatial variables (i.e., a single model for which we divided a day evenly into 6 time periods [4 h each] and included the time of day variables as dummy variables).

Table 1
Independent variables used in the direct-demand models.

Variable		Variable Type	Unit	Bicycle Model		Pedestrian Model	
				Hour-specific[a]	Spatio-temporal[b]	Hour-specific[a]	Spatio-temporal[b]
Land use	Population Density	Area-weighted average	People km^{-2}	X	X	X	X
	Household Income	Area-weighted average	Dollars	X	X	X	X
	Residential Addresses	Count in buffer	Count total	X	X	X	X
	Non-residential Addresses	Count in buffer	Count total	X	X	X	X
	Industrial Area	Area in buffer	Square meters	X	X	X	X
Transportation	Major Roads	Length in buffer	Meters	X	X	X	X
	Local Roads	Length in buffer	Meters	X	X	X	X
	Intersections	Count in buffer	Count total	X	X	X	X
	Bus Stops	Count in buffer	Count total	X	X	X	X
	Sidewalks	Length in buffer	Meters			X	X
	On-street Facility	Length in buffer	Meters	X	X		
	Centrality	Point	Count of O-D pairs	X	X	X	X
Time of day	0:00–4:00	Dummy variable	Hour		X		X
	4:00–8:00	Dummy variable	Hour		X		X
	8:00–12:00	Dummy variable	Hour		X		X
	12:00–16:00	Dummy variable	Hour		X		X
	16:00–20:00	Dummy variable	Hour		X		X

[a] Hour-specific models are an approach to develop a single model for each hour in a day (n = 24 models).
[b] Spatiotemporal models include time of day effects (4 h per interval) as dummy variables in a single model.

Hour-specific models: To replicate previous efforts (i.e., developing models for a specific time period such as the peak hour) we developed hour-specific models (i.e., one model per hour of day) that allowed for different independent variables (e.g., land use and transportation) to be selected for each hour of day. An advantage of these models is that they allow for exploration of which land-use features are most correlated with traffic during different times of day. A disadvantage is that 24 separate models must be developed to capture the entire day.

Spatiotemporal model: To address the limitations of the hour-specific models we developed a single spatiotemporal model that includes temporal factors (i.e., time of day) as dummy variables directly in the model building process. We constructed these variables by dividing the day evenly into 6 time periods (4 h per period) to be candidate variables for selection in our models. An advantage of this approach is that a single model is easier to implement and it is possible to compare the effects of spatial and temporal factors. A disadvantage is that the approach may sacrifice temporal specificity (i.e., produces hourly estimates averaged across a 4-h period rather than individual hourly estimates).

2.3.1. Dependent variable preparation

We previously estimated AADT for bicycles and pedestrians based on the monitoring data described above (Lu et al., 2017). We estimated Annual Average Hourly Traffic (AAHT) for all count locations following a two-step process. First, we created an hourly factor (an average percent of daily traffic value) for each hour and each location using the 7 days of location-specific count data. Second, we multiplied the hourly factor by the location-specific AADT estimates (developed in Lu et al., 2017) to obtain annualized hourly estimates. This process resulted in 24 AAHT estimates of bicycles (pedestrians) for all 101 (72) locations. We tested for normality in the data and log-transformed all AAHT estimates when used as dependent variables for the direct-demand models.

2.3.2. Independent variable selection

We tabulated independent variables for use in the direct-demand models (Table 1). Based on previous literature (Griswold et al., 2011; Molino et al., 2009; Radwan et al., 2016; Miranda-Moreno & Fernandes, 2011; Pulugurtha & Repaka, 2008; Schneider et al., 2009a, 2009b; Wang et al., 2016; Hankey & Lindsey, 2016; Hankey et al., 2017b), we selected variables that capture land use (e.g., industrial areas, residential households) and transportation features (e.g., functional class, bus stops). Variables were tabulated using varying buffer sizes for all 101 count locations (100, 250, 500, 750, 1000, 1250, 1500, 1750, 2000, 2500, 3000 m) following Hankey et al., 2017b. We generated 11 variables at 11 buffer sizes (with one scale-less centrality measure) for the hour-specific models. Additionally, for the spatiotemporal model, we divided the day evenly into 6 time periods (4 h each) and chose the 20:00–23:59 time period (i.e., the time period when mean traffic volumes were nearest to the overall mean among all 6 time periods) as our reference category to code dummy variables. This resulted in a total of 127 (11 × 11 [buffer variables] + 1 [scale-less variable] + 5 [time of day dummy variables]) variables available for selection in the direct-demand models.

2.3.3. Stepwise linear regression approach

We employed a stepwise linear regression approach that allows for predictor variables to be selected at varying buffer sizes with the goal of developing parsimonious models. The result of this procedure is a model that's best use is spatial prediction of traffic volumes; a disadvantage of the approach is that it may sometimes result in counter-intuitive variables to be selected among models. The approach is described in detail in previous studies of air quality and non-motorized traffic modeling (Hankey & Lindsey, 2016; Su et al., 2009). Our goal was to select independent variables (e.g., land use and transportation) that best correlate with the dependent variables (i.e., AAHT). Generally, the process included two steps: (1) adding the variable that was most correlated with bicycle/pedestrian traffic to the model and (2) adding additional variables that were most correlated with the model residuals. This variable selection process ended when either (1) a variable was not statistically correlated ($p < 0.05$) or (2) the multi-collinearity indicator, Variance Inflation Factor (VIF), was greater than 5.

To better compare model coefficients among variables and modes, we fully normalized the model coefficients. We multiplied the regression coefficients by a factor to generate dimensionless regression coefficients: difference between the 95th and 5th percentile for the independent variable divided by the difference between the 95th and 5th percentile for the dependent variable. The normalized coefficients denote the value of the 95th-5th interval increase of the dependent variable (i.e., AAHT) for each 95th-5th interval increase of the independent variable. One of our goals is to explore how temporal factors impact bicycle and pedestrian traffic as compared to spatial factors. This approach allows for relative comparison among spatial and temporal factors in the model as well as between modes.

2.3.4. Sensitivity analysis

We performed two sensitivity analyses for the spatiotemporal models to explore how temporal variability impacts model performance (i.e., adj-R^2). Our sensitivity analyses included: (1) sensitivity by choice of time periods (i.e., 4-h vs. 6-h intervals [dividing 24 h into 4 time periods instead of 6 time periods]) and (2) sensitivity by choice of day of week (i.e., all days vs. weekdays only vs. weekends only).

2.4. Model validation

We performed two types of model validation to assess model performance based on goodness-of-fit (i.e., adj-R^2). First, we conducted internal validation using scatterplots of observed vs. fitted values for the spatiotemporal models.

Second, we performed a Monte Carlo-based 20% holdout analysis for both the spatiotemporal models and the hour-specific models. We compared the "test" data (the 20% randomly selected hold-out data) to the "build" data (the remaining 80% of the data) by using R^2 as a performance measure. This process was repeated 100 times and average R^2 values were calculated as the validation R^2 for each model.

We also tested spatial autocorrelation of the model residuals for the spatiotemporal models during all hours of the day (i.e., 6 time-period intervals). Specifically, we first used Global Moran's I to assess whether there was spatial autocorrelation present in the model residuals. If this issue existed (Moran's I was statistically significant [$p < 0.05$]), we further applied LISA (Local Indicators of Spatial Association; Anselin, 1995) to check where autocorrelation arose during the specific time periods.

2.5. Temporal and spatial estimates of bicycle and pedestrian traffic

We applied the spatiotemporal models to estimate bicycle and pedestrian AAHT during each time period for all street and trail segments in Blacksburg, VA (n = 1848; excluding freeways where bicycles and pedestrians are prohibited). Then, we mapped the AAHT estimates for each time period and examined the spatial patterns of bicycle and pedestrian traffic across the entire transportation network by time of day.

3. Results

We present results from our two sets of direct-demand models (i.e., hour-specific and spatiotemporal models) in Blacksburg, VA. Then, we show model performance and sensitivity analyses associated with choice of time periods and day of week for the spatiotemporal models. After reporting internal and external validation results, we map the bicycle and pedestrian AAHT estimates on the entire transportation network.

3.1. Summary of AAHT at count sites

Using the approach described above, we obtained 2424 (101 locations × 24 h) individual estimates of bicycle AAHT and 1728 (72 locations × 24 h; there were fewer locations with pedestrian estimates due to lack of sidewalks) estimates of pedestrian AAHT (Fig. 2). Since Blacksburg is a small town, the mean (median) AAHT was relatively small (especially during nighttime). Traffic volumes were expectedly higher during the day (i.e., 6:00–21:00). Hourly pedestrian traffic was generally higher than bicycle traffic.

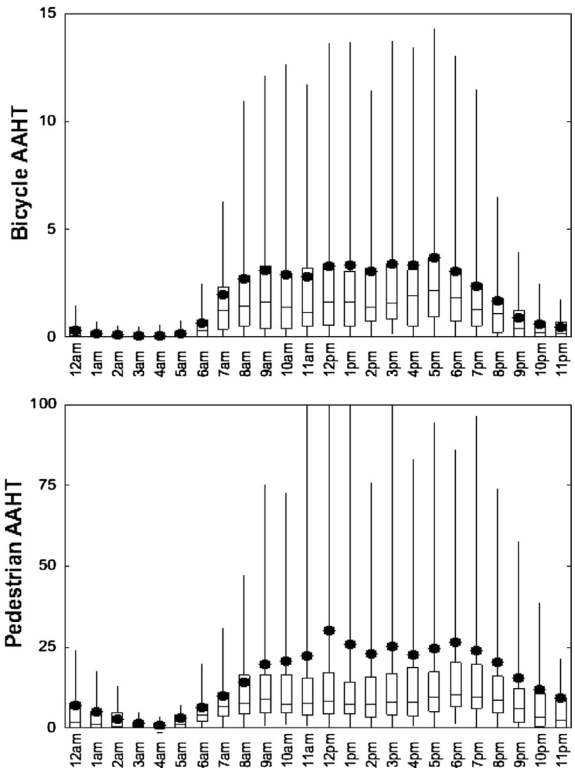

Fig. 2. Boxplots of bicycle and pedestrian AAHT estimates among all count locations. The dot in each figure represents the mean AAHT for that hour.

3.2. Direct-demand models

3.2.1. Hour-specific models

The hour-specific models resulted in 24 individual models each for bicycles and pedestrians. The bicycle models generally selected land use and transportation variables (e.g., population density and on-street facilities) during daytime hours (6:00–21:00); similar variables (e.g., population density and sidewalks) were selected in the pedestrian models. During early morning and late night hours, few (0–2) variables were selected in the models. This finding is likely due to the very low traffic volumes (and thus low spatial variability) during those time periods and warrants caution when applying models for those hours of day. Overall, hour-specific models had modest goodness-of-fit (mean adj-R^2 for bicycle [pedestrian] models during daytime hours: 0.47 [0.69]).

Selected independent variables mostly followed a priori assumptions. For example, hourly bicycle traffic was positively correlated with population density and network centrality. We also observed positive correlation for on-street facilities suggesting the beneficial effects of bicycle infrastructure on cycling rates. The result that household income was negatively correlated with bicycle traffic was possibly due to the spatial location of higher income neighborhoods (i.e., located outside of the Town center with elevated topography that may inhibit cycling activities).

Similarly, pedestrian hourly traffic was positively correlated with population density and bus stops. Sidewalks showed positive correlation indicating the utility of walkable infrastructure. Pedestrian traffic was also negatively correlated with household income and residential addresses. Tables 2 and 3 show the model results for all hour-specific models of bicycles and pedestrians separately.

3.2.2. Spatiotemporal models

The spatiotemporal models included the same set of land-use and transportation variables as candidates for selection, but also added 5 time of day dummy variables (in 4-h intervals) to account for temporal variability. The bicycle model resulted in 7 variables (4 were temporal variables) selected while the pedestrian model selected 15 variables (5 were temporal variables). The overall goodness-of-fit for the spatiotemporal models for the two modes were reasonable (adj-R^2 for bicycle [pedestrian]: 0.49 [0.72]).

Hourly bicycle traffic was positively correlated with all categories of the independent variables, for example, the model selected population density (land-use), on-street facilities and centrality (transportation network features), and two time of day variables (12:00–16:00 and 16:00–20:00; temporal variability). Night (0:00–4:00) and early morning (4:00–8:00) were negatively correlated with bicycle traffic, as expected. Overall, land-use and transportation factors were associated with cycling volumes and the temporal effect (i.e., time of day) also played an important role.

Compared to the bicycle model, the pedestrian model selected more land-use and transportation variables as well as time of day factors, most of which followed a priori assumptions in terms of sign of coefficients. For example, population density, sidewalks,

Table 2
Direct-demand model results for the hour-specific models of bicycle traffic.

Normalized coefficient (buffer size [m])[a]												
Time	Population Density	Income	Residential	Non-residential	Industrial	Local Roads	Intersections	Bus Stops	On-street Facility	Centrality	Intercept[c]	Adj-R^2
0:00–1:00											0.23	0.00
1:00–2:00											0.13	0.00
2:00–3:00										0.41	0.04	0.17
3:00–4:00								0.32 (100)			0.04	0.12
4:00–5:00											0.07	0.00
5:00–6:00	0.13 (100)	−0.37 (1750)	−0.30 (500)	0.34 (500)	−0.11 (100)			0.38 (250)	0.39 (1250)		0.30	0.40
6:00–7:00	0.34 (1250)									0.35	0.13	0.27
7:00–8:00		−0.21 (750)					−0.15 (100)	0.20 (100)	0.32 (1000)	0.31	0.78	0.51
8:00–9:00								0.36 (1000)	0.19 (100)	0.36	0.41	0.49
9:00–10:00		−0.25 (250)						0.12 (100)	0.30 (1000)	0.31	0.86	0.50
10:00–11:00		−0.31 (250)							0.26 (500)	0.25	1.06	0.44
11:00–12:00	0.38 (1250)								0.20 (250)	0.37	0.30	0.48
12:00–13:00		−0.32 (250)							0.21 (750)	0.28	1.12	0.45
13:00–14:00		−0.20 (250)					−0.18 (100)	0.14 (100)	0.31 (1000)	0.28	1.02	0.50
14:00–15:00		−0.31 (250)							0.23 (250)	0.28	1.14	0.39
15:00–16:00	0.34 (1250)								0.20 (500)	0.35	0.44	0.47
16:00–17:00	0.30 (1250)					−0.13 (100)			0.20 (250)	0.35	0.63	0.46
17:00–18:00	0.22 (1250)	−0.17 (100)				−0.15 (100)			0.16 (100)	0.32	1.09	0.49
18:00–19:00	0.30 (1250)					−0.18 (100)			0.18 (250)	0.35	0.70	0.51
19:00–20:00	0.30 (1250)					−0.13 (100)			0.16 (100)	0.36	0.52	0.51
20:00–21:00	0.44 (1250)								0.19 (100)	0.40	0.16	0.57
21:00–22:00	0.57 (1250)										0.14	0.34
22:00–23:00											0.36	0.00
23:00–23:59											0.31	0.00

[a] N = 101; mean adj-R^2 (6:00–21:00) = 0.47.
[c] Intercept cannot be normalized.

Table 3
Direct-demand model results for the hour-specific models of pedestrian traffic.

Normalized coefficient (buffer size [m])[b]											
Time	Population density	Income	Residential	Non-residential	Major roads	Local roads	Intersections	Bus stops	Sidewalks	Centrality	Intercept[c]	Adj-R^2
0:00–1:00											1.16	0.00
1:00–2:00											1.03	0.00
2:00–3:00											0.84	0.00
3:00–4:00	0.24 (250)							0.67 (1000)			−0.33	0.74
4:00–5:00	0.19 (250)	−0.25 (250)						0.30 (250)	0.92 (750)	0.13	−0.46	0.78
5:00–6:00											0.88	0.00
6:00–7:00	0.21 (250)		−0.29 (1000)		0.34 (100)	0.29 (100)			0.62 (750)		0.52	0.70
7:00–8:00	0.13 (250)	−0.27 (1750)	−0.18 (1000)		0.15 (100)				0.51 (750)		1.93	0.63
8:00–9:00		−0.31 (1750)							0.50 (750)		2.24	0.54
9:00–10:00	0.13 (2 5 0)	−0.25 (1750)	−0.15 (1000)						0.61 (750)		2.23	0.65
10:00–11:00	0.14 (500)	−0.19 (1750)	−0.15 (1000)						0.69 (750)		1.92	0.69
11:00–12:00	0.10 (250)	−0.21 (2000)	−0.21 (1000)					0.13 (250)	0.62 (750)		2.14	0.75
12:00–13:00		−0.17 (1750)	−0.42 (1000)					0.27 (250)	0.86 (750)		2.17	0.72
13:00–14:00		−0.16 (3000)					−0.14 (250)		0.80 (750)		2.07	0.75
14:00–15:00		−0.22 (2000)							0.74 (750)		1.82	0.72
15:00–16:00	0.12 (250)	−0.20 (2000)	−0.16 (1000)		0.11 (250)				0.59 (750)		2.00	0.75
16:00–17:00		−0.21 (2000)							0.72 (750)		1.93	0.66
17:00–18:00	0.21 (750)	−0.23 (1750)	−0.20 (1000)		0.14 (250)				0.53 (750)		2.07	0.74
18:00–19:00	0.24 (750)	−0.15 (2000)	−0.23 (1000)	0.09 (100)				0.13 (250)	0.46 (750)		2.21	0.71
19:00–20:00	0.20 (750)	−0.14 (3000)							0.47 (750)		2.05	0.62
20:00–21:00	0.27 (750)		0.16 (100)						0.47 (750)		1.03	0.67
21:00–22:00	0.30 (750)		0.17 (100)		0.13 (250)				0.56 (750)		0.26	0.78
22:00–23:00								0.21 (250)	0.83 (750)		0.30	0.70
23:00–23:59											1.33	0.00

[b] N = 72; mean adj-R^2 (6:00–21:00) = 0.69.
[c] Intercept cannot be normalized.

Table 4
Direct-demand model results for the spatiotemporal models of bicycle and pedestrian traffic.

		Normalized coefficient (buffer size [m])	
		Bicycle model	Pedestrian model
Land use	Population density	0.30 (1250)	0.12 (250)
	Household income		−0.14 (2000)
	Residential addresses		−0.15 (1000)
	Non-residential addresses		0.04 (100)
	Industrial area		−0.02 (2000)
Transportation	Major roads		0.17 (250)
	Local roads		0.13 (100)
	Intersections		−0.14 (250)
	Bus stops		0.14 (250)
	Sidewalks		0.53 (750)
	On-street facility	0.16 (250)	
	Centrality	0.28	
Time of day	0:00–4:00	−0.27	−0.22
	4:00–8:00	−0.17	−0.14
	8:00–12:00		0.13
	12:00–16:00	0.15	0.13
	16:00–20:00	0.15	0.17
Intercept		0.27	1.24
N		2424	1728
Adj-R^2		0.49	0.72

major roads, and local roads were positively correlated with pedestrian traffic; three time of day variables (8:00–12:00, 12:00–16:00, and 16:00–20:00) were also selected. Pedestrian traffic was negatively correlated with household income, industrial area as well as night (0:00–4:00) and early morning (4:00–8:00). Intersection density, however, showed a negative correlation, possibly due to multicollinearity with retail area and fewer intersections on the university campus. Table 4 shows the model results of the spatiotemporal models.

3.2.3. Comparison among models

Both the hour-specific and spatiotemporal models selected land-use and transportation variables with expected signs and resulted in reasonable goodness-of-fit (mean adj-R^2 for hour-specific [spatiotemporal] bicycle model: 0.47 [0.49]; pedestrian model: 0.69 [0.72]). This indicates the choice of independent variables accounted for a reasonable portion of the variability in hourly bicycle and pedestrian traffic. The model results echo findings of other studies (Griswold et al., 2011; Molino et al., 2009; Radwan et al., 2016; Miranda-Moreno & Fernandes, 2011; Pulugurtha & Repaka, 2008; Schneider et al., 2009a, 2009b; Wang et al., 2016; Hankey & Lindsey, 2016; Hankey et al., 2017b). However, differences existed in variable selection between both transportation mode (i.e., bicycle vs. pedestrian models) and model type (i.e., spatiotemporal vs. hour-specific models). For example, the spatiotemporal bicycle model selected fewer independent variables than the hour-specific bicycle models. This was likely due to the fact that the hour-specific models consisted of 24 individual models for separate hours and thus variable selection was not always consistent among models. The spatiotemporal pedestrian model selected nearly all of the candidate variables and temporal factors while each of the hour-specific models generally selected fewer variables. Overall, the spatiotemporal models performed better than the hour-specific models in (1) goodness-of-fit and (2) building more parsimonious models that directly incorporate temporal variability (i.e., only one model per mode).

We compared the mean fully normalized coefficients among modes and model types for land-use and transportation features vs. temporal factors on bicycle and pedestrian traffic. This exercise potentially offers insight into the influence of different types of variables on hourly traffic patterns. Mean absolute fully normalized regression coefficients for the hour-specific (spatiotemporal) bicycle models were 0.27 (0.30) for land use variables and 0.23 (0.22) for transportation variables, as compared to temporal variables: 0.19 (spatiotemporal model only). In general, the magnitude of effect of the temporal factors is similar to the land use and transportation variables.

Mean absolute fully normalized regression coefficients for the hour-specific (spatiotemporal) pedestrian models were 0.18 (0.09) for land use variables and 0.28 (0.23) for transportation variables, as compared to temporal variables: 0.16 (spatiotemporal model only). Sidewalks had the highest mean absolute fully normalized coefficients (hour-specific [spatiotemporal]: 0.64 [0.53]) indicating the positive effect of pedestrian infrastructure. Also, temporal factors had a similar magnitude of effect as land use and transportation variables. Fig. 3 shows the fully normalized regression coefficients among the direct-demand models.

3.2.4. Sensitivity analysis

We performed a series of sensitivity analyses for the spatiotemporal models by varying two aspects of our modeling approach: (1) aggregation method for time of day variables (i.e., grouping time of day in 6-h instead of 4-h periods) and (2) modeling different

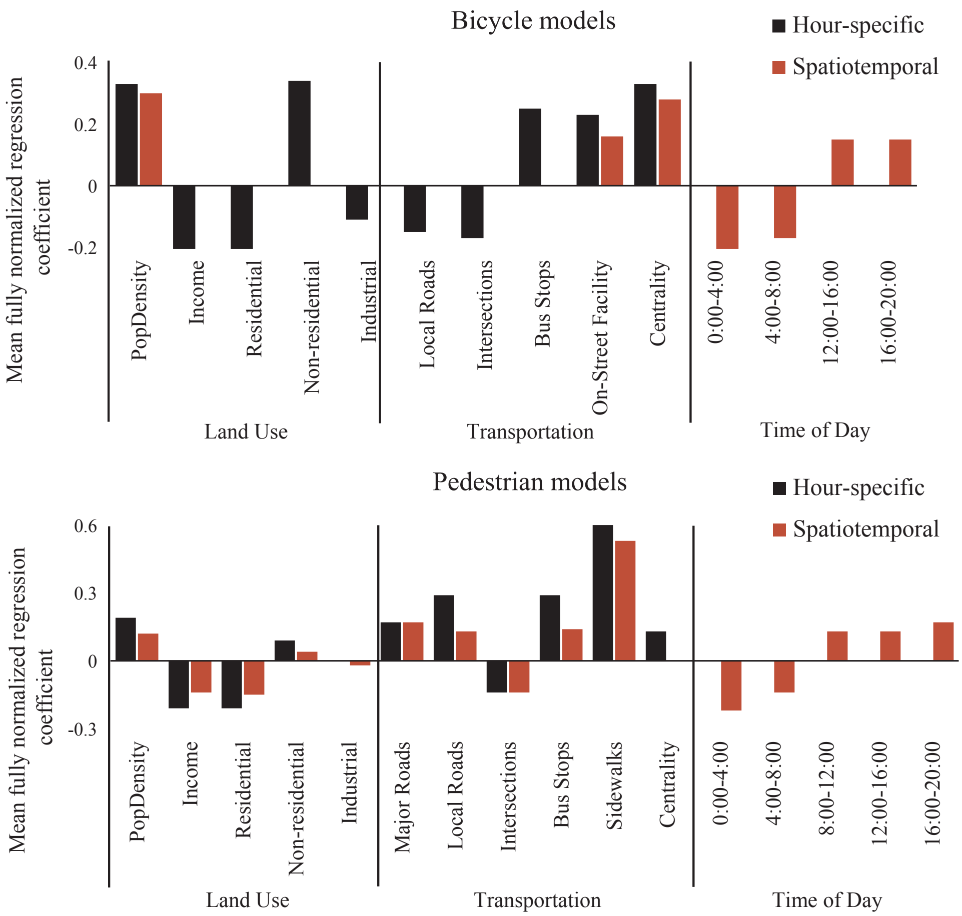

Fig. 3. Mean fully normalized regression coefficients of hour-specific and spatiotemporal models.

days-of-week (i.e., all days vs. weekdays only vs. weekends only). For the time of day aggregation method, the 6-h spatiotemporal models showed slightly higher adj-R^2 (bicycle [pedestrian]: 0.55 [0.72]) than the 4-h spatiotemporal models ((bicycle [pedestrian]: 0.49 [0.72]). However, the improvement of the adj-R^2 for the bicycle model was likely the result of selecting many more land use and transportation variables (11 vs. 3) thus potentially jeopardizing the usefulness for practitioners. Additionally, the 6-h approach results in loss of time resolution in the traffic estimates. The alternate aggregation method (i.e., dividing the day into fewer intervals [6-h vs. 4-h]) didn't result in a large change in model performance.

When varying the day of week for modeling, the models for all days (the base-case models presented in this paper) performed better than the weekday or weekend models. The adj-R^2 of the bicycle (pedestrian) models were: 0.49 (0.72) for all days, 0.47 (0.71) for weekdays, and 0.27 (0.64) for weekends. The difference between weekday and weekend model performance could be attributable to the fact that we had only 1 week of monitoring at each location and thus stratifying the sample in this way introduces uncertainty

Table 5
Sensitivity analysis of bicycle and pedestrian spatiotemporal models.

	Bicycle model		Pedestrian model	
	Method of aggregation for time-of-day variables			
	4-h model	6-h model	4-h model	6-h model
Number of spatial variables selected	3	11	10	11
Adj-R^2	0.49	0.55	0.72	0.72
	Modeling different days-of-week			
Adj-R^2 for all days	0.49		0.72	
Adj-R^2 for weekdays	0.47		0.71	
Adj-R^2 for weekends	0.27		0.64	

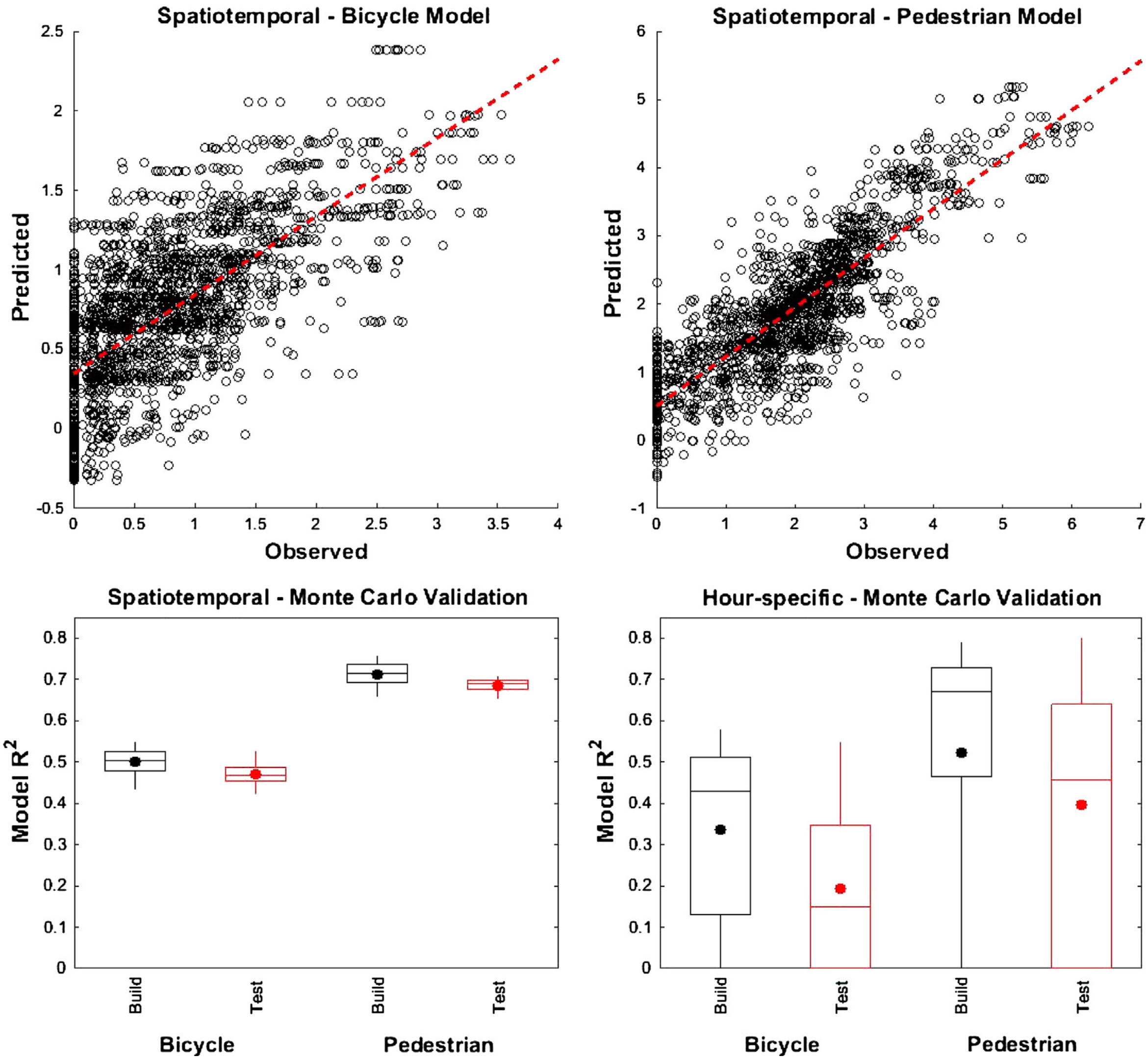

Fig. 4. Internal (top panels) and external (bottom panels) validation of bicycle and pedestrian traffic models.

(i.e., traffic estimates are based on fewer days of data) in the specification of the dependent variable in our models. Table 5 shows the results of the sensitivity analysis of the spatiotemporal models.

3.3. Model validation

We explored model performance (i.e., goodness-of-fit) by conducting two validation exercises: internal validation (scatterplots of observed vs. fitted traffic estimates) and external validation (a 20% Monte Carlo-based hold-out analysis). Our models had similar goodness-of-fit as previous efforts (Fagnant & Kockelman, 2016; Hankey & Lindsey, 2016; Miranda-Moreno & Fernandes, 2011; Pulugurtha & Repaka, 2008; Schneider et al., 2009a, 2009b; Wang et al., 2016). The spatiotemporal models had relatively consistent validation R^2 results from our hold-out analysis. However, the hour-specific models tended to be unstable when applying the hold-out validation. This could be attributable to the sample size for each approach; the 4-h models had a larger sample size (n = 1728–2424 for a single model) than the hour-specific models (n = 72–101 for 24 separate models). Additionally, a slight drop in model performance between the “test” and “build” data set occurred for both models. This finding suggests that our results may be sensitive to choice of traffic monitoring locations. Fig. 4 shows the results of the internal and external validation for both models.

We used Global Moran’s I to test for autocorrelation among the residuals of the bicycle and pedestrian spatiotemporal models. Global Moran’s I was statistically significant ($p < 0.05$) for the bicycle (pedestrian) spatiotemporal models during the 8:00–12:00 (20:00–23:59) time period; bicycle (pedestrian) Moran’s I: 0.22 (0.10), which indicated that spatial autocorrelation existed during these time periods. Therefore, we further applied LISA (Anselin, 1995) and found that spatial clustering of model residuals existed for a small number of locations on the east side of the university campus indicating that our models do not fully capture the variability in

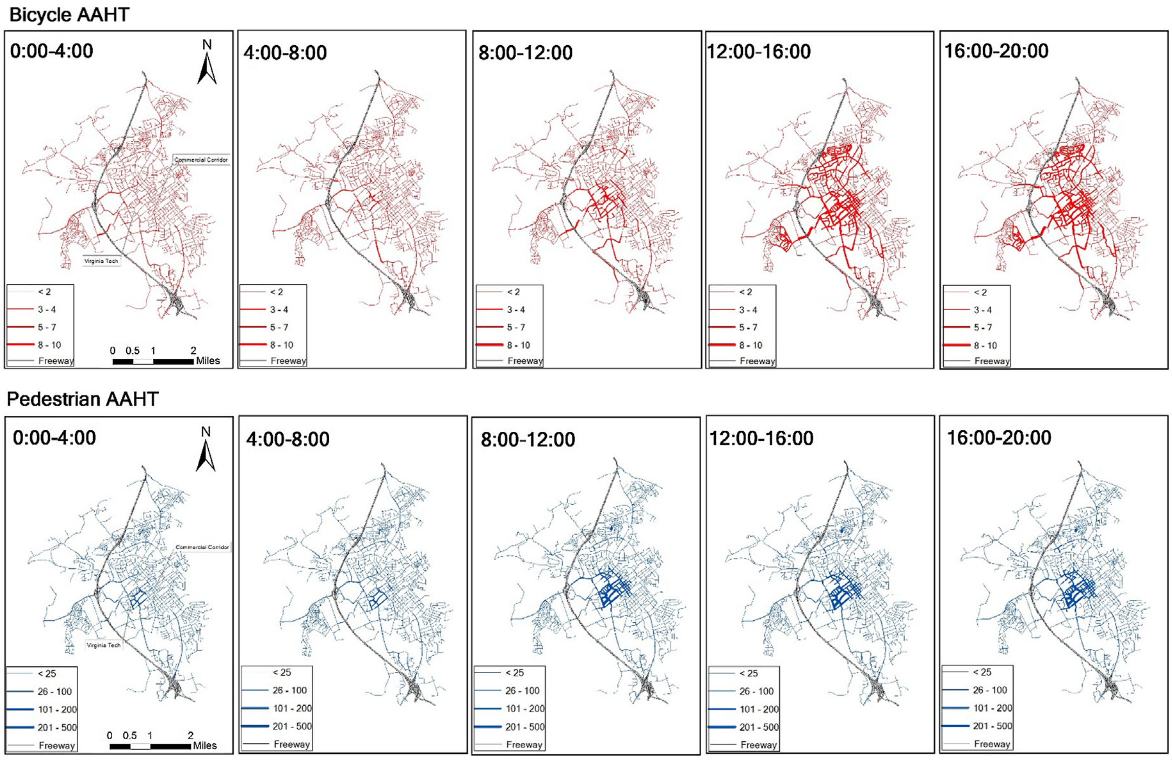

Fig. 5. Model-derived bicycle and pedestrian AAHT estimates for all street and trail segments in Blacksburg using the spatiotemporal models.

those locations. Details of the spatial autocorrelation process are shown in Appendix A, Table A.1 and Figs. A.1, A.2.

3.4. *Temporal and spatial estimates of bicycle and pedestrian traffic at unmonitored locations*

We mapped bicycle and pedestrian AAHT estimates for all street and trail segments (n = 1848) in Blacksburg for all 6 time of day intervals (Fig. 5). Bicycle and pedestrian traffic varied spatially with each mode. Bicycle volumes were highest on off-street trails and corridors connected to the university campus and commercial areas. Pedestrian traffic clustered on the university campus and the surrounding commercial corridors. These spatial patterns indicate that cyclists were more dispersed throughout the Town while pedestrian volumes were more correlated with university and commercial areas.

When adding temporal information to the spatial models, both bicycle and pedestrian traffic showed similar temporal variations among the different times of day (e.g., demand for both modes increased from early morning and peaked during the daytime, but decreased during the nighttime). However, minor differences existed. For example, bicycle traffic peaked between 12:00–20:00 and clustered on the university campus as well as off-street trails with access to the campus. Cyclists also appeared to use the connecting trails during the night (i.e., 20:00–23:59). These findings suggest that hazard exposure (e.g., crash risk) may be a concern on these trails at night where inadequate lighting exists along these trails. For pedestrians, volumes increased more rapidly on the university campus than cyclists especially in the morning (i.e., 8:00–12:00). Furthermore, pedestrians also clustered on the campus and commercial corridors at night (i.e., 20:00–23:59) indicating these areas may require more attention regarding safety-related infrastructure (e.g., lights) during nighttime hours.

4. Discussion

We developed two types of direct-demand models that include temporal information based on data from a comprehensive traffic monitoring program with bicycle (pedestrian) counts at 101 (72) locations in a small, rural college town. Our work aims to estimate hourly bicycle and pedestrian traffic and provide opportunities for subsequent research into exposure to hazards (e.g., air pollution and traffic crashes). Our study also explores the relative magnitude of correlation of both temporal (e.g., time of day) and spatial (land use and transportation network) variables with bicycle and pedestrian traffic volumes.

A key contribution of our direct-demand models is to explore how temporal variability (i.e., time of day) impacts spatial patterns of traffic. For example, we were able to build individual models of bicycle and pedestrian traffic for each hour (i.e., n = 24 h-specific models) and found that major land use (e.g., population density) and transportation (e.g., centrality, on-street facility, sidewalks) variables were correlated with non-motorized traffic during many hours of the day. By assembling the time of day variables as dummy variables, we developed spatiotemporal models and found that temporal factors were as important as traditional spatial variables (e.g., land use and transportation factors) in predicting traffic volumes. These findings are consistent with previous studies (Fagnant & Kockelman, 2016; Hankey & Lindsey, 2016; Miranda-Moreno & Fernandes, 2011; Pulugurtha & Repaka, 2008; Schneider et al., 2009a, 2009b; Wang et al., 2016; McDaniel et al., 2014) and further underscore the importance of temporal factors in predicting bicycle and pedestrian traffic.

Most direct-demand models have been developed based on estimates of AADT or counts of peak hours (Schmiedeskamp & Zhao, 2016; Tabeshian & Kattan, 2014; Hankey & Lindsey, 2016; Hankey et al., 2017b). Adding temporal information allows for development of spatial models for targeted hours of day (hour-specific models) or for integrating effects of both temporal and spatial factors in a single model (spatiotemporal model). As the model results indicate, the spatiotemporal models performed better than the hour-specific models in (1) goodness-of-fit (bicycle adj-R^2: 0.49 vs. 0.47; pedestrian adj-R^2: 0.72 vs. 0.69) and (2) adding temporal information in a user-friendly way (a single model designed for 4-h periods of a day vs. 24 individual models for each hour of the day). These temporal models make it possible to compare to previous models that used daily average (e.g., adj-R^2 of daily bicycle [pedestrian]: 0.52 [0.71]; Hankey et al., 2017b) or peak-hour counts (e.g., adj-R^2 of peak-period bicycle [pedestrian]: 0.46 [0.50]; Hankey & Lindsey, 2016).

By combining the results of our direct-demand models with information on hazards (e.g., crashes or air toxics), researchers could explore spatiotemporal patterns of exposure. For example, the non-motorized estimates of off-peak hours could be used to explore crime risks or the economic and recreational activities of cyclists and pedestrians at night (e.g., activity near restaurants or entertainment districts). Furthermore, our models could provide spatiotemporal estimates of bicycle and pedestrian traffic for buildout of safety-related infrastructure (e.g., bike lanes, sidewalks, traffic signals, or street lights) or to inform planning decisions aimed at health-promoting interventions (e.g., bike sharing systems).

Our work demonstrates that it is possible to develop spatiotemporal models of non-motorized traffic as an input to exposure assessment analyses that would benefit from having both spatially and temporally resolved estimates of bicycle and pedestrian traffic. However, future research could expand our work in several ways. For example, a limitation of our study is that our data was collected in a small, college town where bicycle and pedestrian volumes are relatively small (especially during nighttime or early morning). This suggests that further replication of our work in larger communities (where we expect more non-motorized traffic and larger mode share during those hours) or in a small town without a university (where most cycling and walking activities may not come from university users) is warranted. Further work could adapt our approach to include data from emerging technologies (e.g., GPS-enabled fitness tracking apps) which provide rich information on the spatiotemporal patterns of active travel. Lastly, prior studies of direct-demand modeling for bicycles and pedestrians use a wide variety of statistical models, e.g., linear regression (Jones et al., 2010; Lindsey et al., 2006; Schneider et al., 2009b), Poisson or negative binomial regression (Wang et al., 2014; Merom et al., 2003), generalized linear mixed models (Chen et al., 2017) or geographically weighted regression (Yang et al., 2017). We used stepwise linear regression to compare our results to relevant previous studies (Jones et al., 2010; Lindsey et al., 2006; Schneider et al., 2009b); however, a useful research topic would be to systematically evaluate multiple modeling approaches on the same dataset to evaluate the impacts of these modeling choices.

5. Conclusions

We developed two types of temporally-resolved direct-demand models of bicycle and pedestrian traffic (i.e., hour-specific models and spatiotemporal models) based on a comprehensive non-motorized traffic monitoring campaign in Blacksburg, VA. We confirmed that traditional land use (e.g., population density) and transportation (e.g., on-street facility, sidewalks) variables were correlated with bicycle or pedestrian traffic at varying spatial scales. We also found that temporal (i.e., time of day) variables had a similar magnitude of correlation as the spatial (i.e., land use and transportation) variables. Specifically, the mean fully normalized regression coefficients were 0.19 (temporal) vs. 0.26 (spatial) for the bicycle models and 0.16 (temporal) vs. 0.16 (spatial) for the pedestrian models. Our models had reasonable goodness-of-fit (adj-R^2 for hour-specific [spatiotemporal] bicycle model: $\sim$0.47 [0.49]; pedestrian model: $\sim$0.69 [0.72]). The spatiotemporal models may provide a more user-friendly option for generating spatiotemporal estimates of bicycle and pedestrian traffic as compared to the hour-specific models (i.e., a single model vs. 24 h-specific models). We produced spatial estimates for all street and trail segments (n = 1848) in Blacksburg and found that spatial patterns of cyclists and pedestrians varied by mode and time of day. Results from our approach could be used to assess time-resolved patterns of exposure to air toxics or traffic accidents and to prioritize safety-related or health-promoting infrastructure (current analyses focus on time-averaged estimates). Our work serves as a proof-of-concept that direct-demand modeling can be modified to include temporal information to accurately estimate hourly non-motorized traffic volumes for targeted time periods on an entire transportation network.

Acknowledgements

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Appendix A. Spatial Autocorrelation of the Spatiotemporal Models

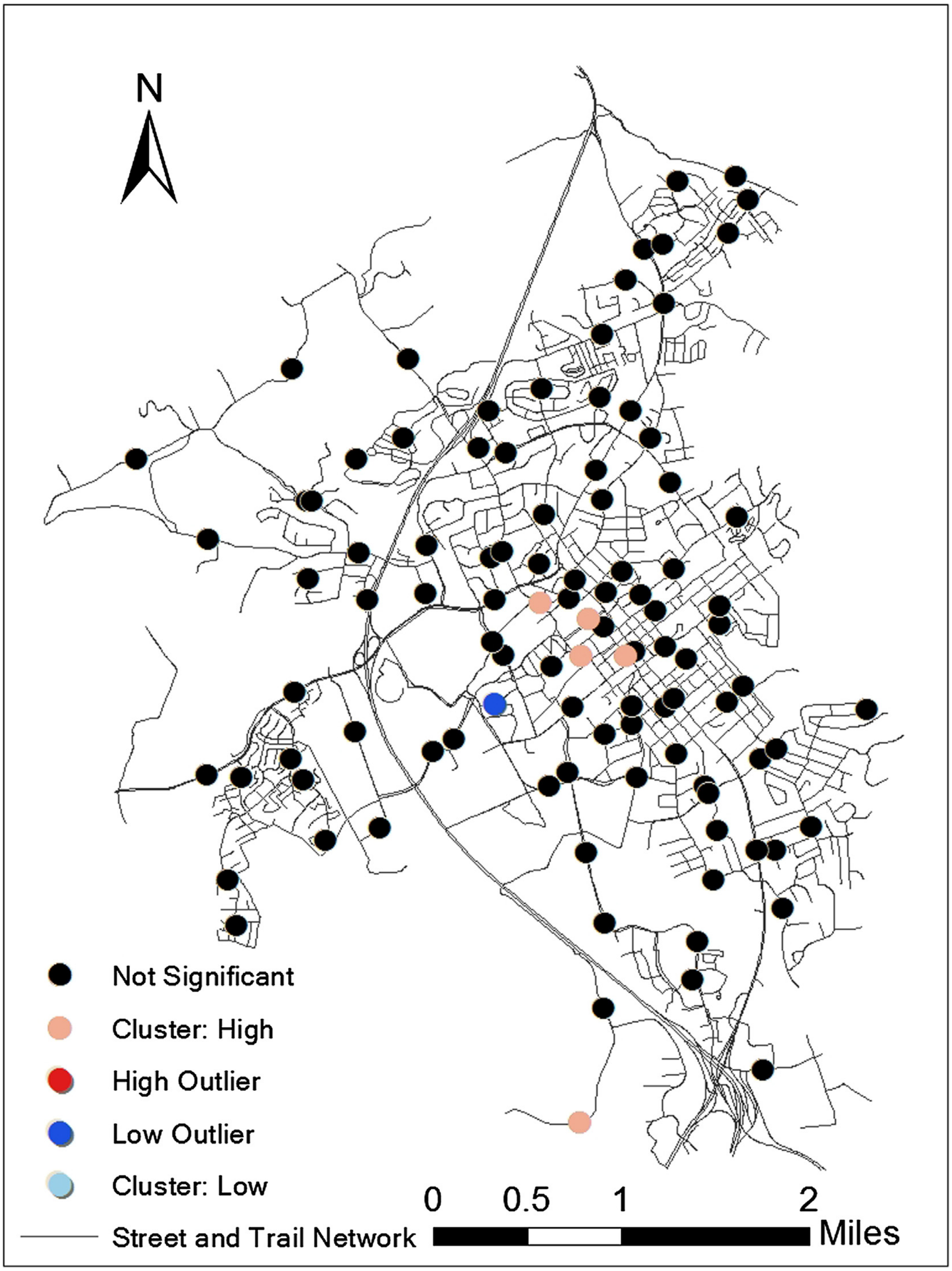

Fig. A1. LISA of bicycle spatiotemporal models during 8:00–12:00.

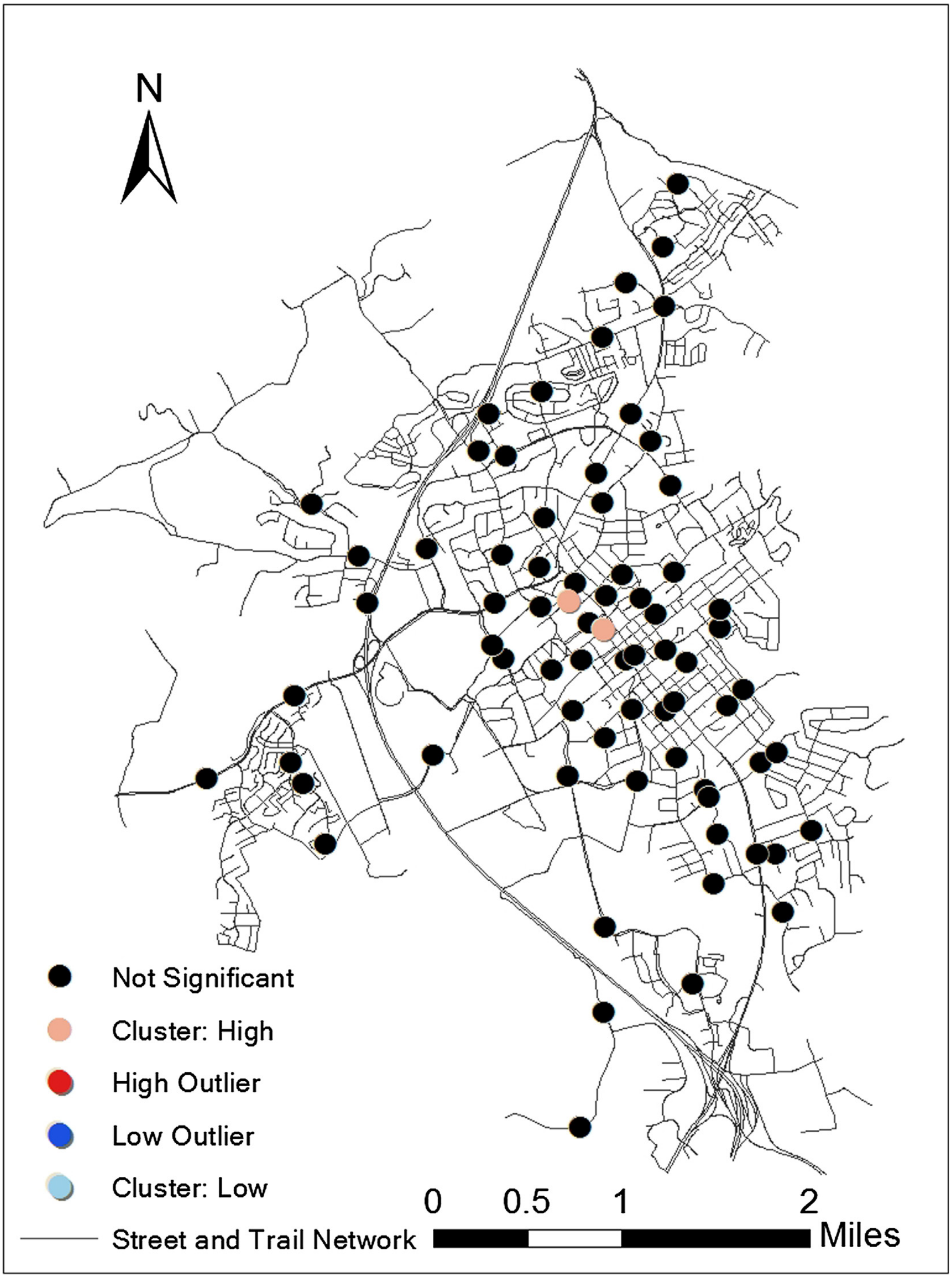

Fig. A2. LISA of bicycle spatiotemporal models during 20:00–23:59.

Table A.1
Summary of Moran's I of the spatiotemporal models for bicycles and pedestrians.

Mode	Time of day	Moran's I	p-value
Bicycle	0:00–4:00	0.10	0.18
	4:00–8:00	0.04	0.56
	8:00–12:00	0.22	0.01*
	12:00–16:00	0.10	0.16
	16:00–20:00	0.01	0.85
	20:00–23:59	0.11	0.15
Pedestrian	0:00–4:00	0.05	0.26
	4:00–8:00	−0.06	0.64
	8:00–12:00	−0.14	0.05
	12:00–16:00	0.12	0.08
	16:00–20:00	−0.02	0.92
	20:00–23:59	0.10	0.01*

* Denotes the residual was statistically significant ($p < 0.05$). The distance band is set at 500 m.

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2018.05.011.

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