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Spatial models of active travel in small communities: Merging the goals of traffic monitoring and direct-demand modeling

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ABSTRACT

A number of recent studies have made progress on specific components of monitoring and modeling bicycle and pedestrian traffic. However, few efforts merge the goals of collecting traffic counts and developing spatial models to meet multiple objectives, e.g., tracking performance measures and spatial modeling for use in exposure assessment. We used estimates of bicycle and pedestrian Annual Average Daily Traffic (AADT) from a comprehensive traffic monitoring campaign in a small community to develop direct-demand models of bicycle and pedestrian AADT. Our traffic monitoring campaign (101 locations) was designed specifically to capture spatial variability in traffic patterns while controlling for temporal bias. Lacking existing counts of cyclists and pedestrians, we chose count sites based on street functional class and centrality (a measure of trip potential). Our direct-demand models had reasonable goodness-of-fit (bicycle R^2: 0.52; pedestrian R^2: 0.71). We found that aspects of the transportation network (bicycle facilities, bus stops, centrality) and land use (population density) were correlated with bicycle and pedestrian AADT. Furthermore, spatial patterns of bicycle and pedestrian traffic were different, justifying separate monitoring and modeling of these modes. A strength of our analysis is that we conducted counts at a representative sample of all street and trail segments in our study area (Blacksburg, Virginia; ~5.5% of segments) – an advantage of monitoring in a small community. We demonstrated that it is possible to design traffic monitoring campaigns with multiple goals (e.g., estimating performance measures and developing spatial models). Outputs from our approach could be used to (1) assess land use patterns that are correlated with high rates of active travel and (2) provide inputs for exposure assessment (e.g., calculating crash rates or exposure to other hazards). Our work serves as a proof-of-concept on a relatively small transportation network and could potentially be extended to larger urban areas.

1. Introduction and literature review

Efforts to build healthy, sustainable transportation systems often include provisions for increasing rates of active travel (i.e., cycling and walking; Nieuwenhuijsen and Khreis, 2016). Integrating routine counts of cyclists and pedestrians in traffic monitoring campaigns is an ongoing effort and would allow planners and engineers to track performance measures for all modes when making decisions on investments in infrastructure. Developing methods to model spatial patterns of bicycle and pedestrian traffic flows (based on the counts collected in the traffic monitoring campaigns) could be used for multiple goals including: (1) assessing land use

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patterns that are correlated with high rates of active travel and (2) providing necessary inputs for exposure assessment (e.g., calculating crash rates or exposure to other hazards).

Tracking performance measures, for example, Annual Average Daily Traffic (AADT), is an important method for evaluating transportation systems and allocating funding for future infrastructure. Historically, efforts to collect traffic counts and model performance measures have focused on motor vehicles (FHWA, 2010); exploratory studies have introduced potential metrics to measure risk for bicycles and pedestrians (Molina et al., 2009). Emerging efforts aim to adapt traffic count procedures and modeling techniques to also collect and model information on bicycle and pedestrian traffic patterns (Lindsey et al., 2014). However, for bicycles and pedestrians, most of these efforts have not focused on designing traffic monitoring programs specifically for the purpose of spatial modeling.

Over the past decade researchers have developed best practices for implementing traffic monitoring programs for bicycles and pedestrians. Guidance has emerged on specific components of monitoring, for example, tradeoffs between short-duration count length and AADT estimation error, (Hankey et al., 2014; Nordback et al., 2013; Nosal et al., 2014) seasonality of traffic patterns (Lindsey et al., 2016; Wang et al., 2014), and developing scaling factors and factor groups for estimating AADT (Esaway et al., 2013; Miranda-Moreno et al., 2013). Most monitoring programs have focused on single components of the network, e.g., off-street trails (Lindsey et al., 2007; Wang et al., 2014) or corridors of interest (Miranda-Moreno et al., 2013); recent efforts have expanded to comprehensive monitoring of the entire network (DVRPC, 2016; Lu et al., 2017). Many of the findings from these programs have been summarized in federal guidance documents (FHWA, 2013; NCHRP, 2014a, 2014b).

Similar to traffic monitoring, spatial modeling of bicycle and pedestrian traffic patterns has become a useful tool in bicycle and pedestrian planning. Resource requirements for integrating bicycles and pedestrians in travel demand models are large; however, progress is being made to develop these inputs (Hood et al., 2011; Iacono et al., 2010; Krizek et al., 2009; NCHRP, 2014a, 2014b). Direct-demand modeling is a statistical-empirical approach that has emerged as an alternative to travel demand modeling. Multiple studies have used existing traffic count databases to develop city-specific direct-demand models (Fagnant and Kockelman 2016; Hankey and Lindsey, 2016; Jones et al., 2010; Miranda-Moreno and Fernandes, 2011; Pulugurtha and Repaka, 2008; Schneider et al., 2009a, 2009b, 2012; Wang et al., 2016). Typically, traffic monitoring programs are not designed specifically for the purpose of spatial modeling and models often reflect spatial and temporal biases associated with the choice of count locations and time period of data collection.

A key need to better assess patterns of bicycle and pedestrian traffic is to integrate spatial modeling as a design criteria in traffic monitoring programs. In this paper, we present direct-demand models of bicycle and pedestrian traffic from a small, rural college town: Blacksburg, Virginia. Our models were developed using counts from a traffic monitoring program that was developed: (1) to estimate performance measures for use in Town planning (a common use of traffic counts) and (2) for building spatial models (as an additional output of traffic monitoring). The traffic monitoring program was developed specifically to estimate AADT as the input for model building and thus better control for temporal variation in traffic. Our work contributes to the literature by illustrating how traffic monitoring programs can be tailored specifically for the purpose of developing spatial models. The outputs of these models can then be used to assess the impact of land use patterns on rates of active travel and as an input to exposure assessment for traffic safety or air quality (Hankey et al., 2017; Jacobsen, 2003; Khreis et al., 2016). Our study area is a small rural college town which allows for (1) exploration of trends in bicycle and pedestrian traffic in a small community (most studies are in large urban areas) and (2) development of a proof-of-concept study for merging traffic monitoring and spatial modeling where it is possible to sample a relatively large portion of the transportation network (i.e., we sampled 5.5% of street and trail segments in Blacksburg) as compared to previous studies (primarily conducted in large urban areas).

2. Data and methods

We used the results of a traffic monitoring campaign in Blacksburg, VA to develop direct-demand models of bicycle and pedestrian AADT. The traffic monitoring campaign resulted in 101 locations with separate estimates of bicycle and pedestrian traffic. Our overarching goal is to demonstrate how traffic monitoring campaigns can be designed for multiple purposes, such as tracking performance measures over time and developing spatial models.

2.1. Study location

Our study area is the small, rural college town of Blacksburg, VA (full-year population: ~12,000; student population: ~30,000). Blacksburg is part of the Blacksburg-Christiansburg-Radford statistical area (population: ~160,000) in the Appalachian Mountains in southwest Virginia. The area is heavily influenced both economically and demographically by Virginia Tech University.

2.2. Site selection and data collection

We collected traffic counts using three types of automated counters: (1) pneumatic tubes for bicycles on streets (MetroCount MC 5600 Vehicle Classifier System), passive infrared for pedestrians on sidewalks (Eco-Counter Pyro), and radiobeam for bicycles and pedestrians on trails (Chambers RadioBeam Bicycle-People Counter). We collected continuous counts for year-2015 at four reference sites to capture temporal trends. We also collected 1-week counts at 97 short-duration count locations for spatial coverage. Using the counts from the four reference sites we developed day-of-year scaling factors (Hankey et al., 2014; Nordback et al., 2013; Nosal et al., 2014) to estimate AADT at the 97 short-duration count sites. Further details on the traffic count campaign and method for estimating

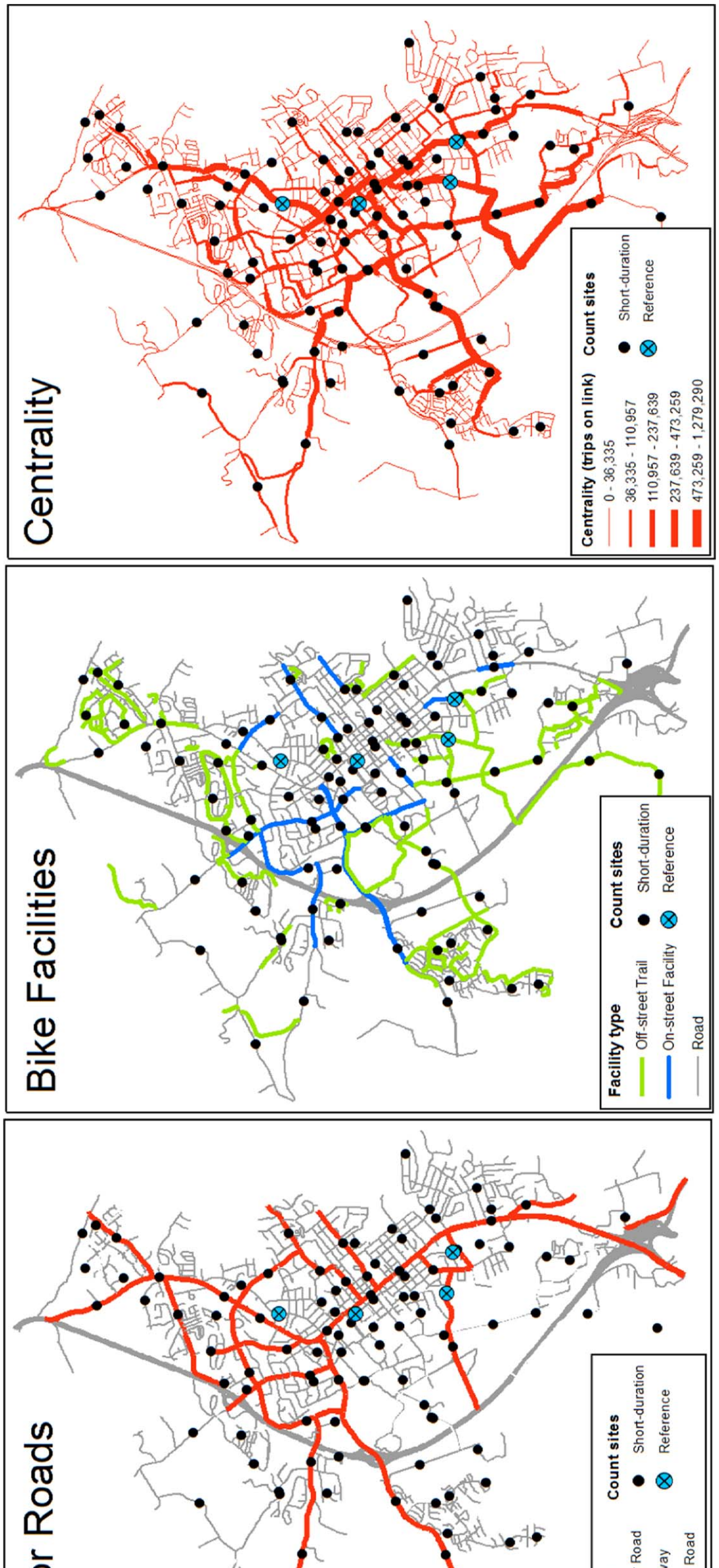

Fig. 1. Bicycle and pedestrian count locations in Blacksburg, VA with criteria used for stratified sampling.

Table 1
Independent variables included in the model building process.

Variable	Variable Type	Unit	Bicycle Model	Pedestrian Model
Major Roads	Length in buffer	Meters	X	X
Local Roads	Length in buffer	Meters	X	X
Centrality	Point	Count of O-D pairs	X	X
Off-street Trail	Length in buffer	Meters	X	X
On-street Facility	Length in buffer	Meters	X	
Sidewalks	Length in buffer	Meters		X
Intersections	Count in buffer	Count total	X	X
Bus Stops	Count in buffer	Count total	X	X
Impervious Surface	Area in buffer	Square meters	X	X
Paved Parking	Area in buffer	Square meters	X	X
Retail Area	Area in buffer	Square meters	X	X
Industrial Area	Area in buffer	Square meters	X	X
Residential Addresses	Count in buffer	Count total	X	X
Non-residential Addresses	Count in buffer	Count total	X	X
Tree Canopy	Area in buffer	Square meters	X	X
Non-tree Vegetation	Area in buffer	Square meters	X	X
Population Density	Area-weighted average	People km^{-2}	X	X
Household Income	Area-weighted average	Dollars	X	X

AADT are given in (Lu et al., 2017). We briefly discuss aspects of the data collection and site selection that are important for spatial modeling but point readers to (Lu et al., 2017) for a detailed description of the count campaign.

We selected count locations to capture spatial variability in bicycle and pedestrian traffic. Specifically, we stratified location selection by street functional class (major road, local road, off-street trail) and used a measure of bicycle trip potential (centrality) to assess whether our count locations captured variability of traffic within each road type. We used a previously published centrality metric (McDaniel et al., 2014) to estimate bicycle trip potential for each segment in the network based on its relative importance for bicycle trips within the overall network. Our approach to select count locations strived to encompass variability for both of the dependent variables (i.e., bicycle and pedestrian AADT) as well as the independent variables (e.g., street functional class, land use, presence of facilities) in our direct-demand models. Fig. 1 shows the count locations in Blacksburg, VA.

2.3. *Direct-demand modeling approach*

Our modeling approach consisted of mainly two steps: (1) compiling land use variables at multiple spatial scales at each count location and (2) employing stepwise linear regression to select variables from step 1 for use as independent variables in each model.

2.3.1. *Independent variable selection*

We performed an inventory of available data for use in the direct-demand models in Blacksburg (Table 1). We included variables that generally capture aspects of the transportation system (e.g., functional class, transit infrastructure) and land use (e.g., retail area, impervious surface, population density). We tabulated the variables for each count location using network buffers of varying spatial scale (100, 250, 500, 750, 1000, 1250, 1500, 1750, 2000, 2500, 3000 m). Each of the variables were then offered for selection in the model building routine described below.

2.3.2. *Stepwise linear regression approach*

We followed the model building approach originally developed for air quality models by Su et al. (2009) and later applied to bicycle and pedestrian traffic by Hankey and Lindsey (2016). We used stepwise linear regression to select significant independent (i.e., land use) variables from the list of candidate independent variables. The variable most correlated with bicycle or pedestrian traffic was added to the model; then, subsequent variables were added that were most correlated with model residuals. This process continued until either a variable was not statistically significant ($p < 0.05$) or the variable violated criteria for multi-collinearity (Variance Inflation Factor [VIF] > 5). Since we tabulated 18 variables at 11 buffer sizes (and had one point variable) there were 199 variables available for selection in the model building process. We restricted selection to a single buffer size per variable (i.e., once a variable was selected at a single buffer size, the algorithm removes that variable at all other buffer sizes as candidate variables for selection). We tested our dependent variable (i.e., bicycle and pedestrian AADT) for normality using untransformed and log-transformed data. We found our data to be lognormally distributed and thus used log-transformed data as the dependent variable in our models.

2.4. *Model validation*

We assessed model performance by goodness-of-fit and scatterplots of observed vs. fitted values for internal validation. We also performed a Monte Carlo-based 20% holdout analysis to estimate a validation R^2 for our models. For the hold-out validation we randomly held out 20% of the AADT estimates ("test" data), built a new model with the remaining 80% of the AADT estimates ("build" data), and compared model estimates to the actual data for the "test" dataset. This process was repeated 100 times and an average R^2 value was calculated and reported as the validation R^2.

2.5. Spatial estimates of pedestrian and bicycle traffic

Using our final models we estimated bicycle and pedestrian AADT for all street and trail segments in Blacksburg (n = 1,848). We mapped all AADT estimates and explored spatial patterns of traffic across the network. Below we discuss spatial patterns of the data as well as potential uses of a spatial surface of bicycle and pedestrian traffic for exposure assessment and in the planning process.

3. Results

We first present findings of direct-demand models for Blacksburg. Then, we discuss model performance and how our approach is a proof-of-concept for developing traffic monitoring campaigns that are designed partially for spatial modeling and partially for tracking performance measures over time.

3.1. Summary of AADT at count sites

Our traffic monitoring campaign resulted in 101 individual estimates of bicycle AADT and 72 estimates of pedestrian AADT. We were unable to obtain pedestrian counts at 29 of the locations due to lack of a sidewalk (our passive infrared counters were only suitable for counting on sidewalks); many low density, residential streets in Blacksburg do not have a sidewalk. AADT was correlated with street functional class for bicycles, with the highest traffic volumes on off-street trails, followed by major roads, and local roads. Pedestrian traffic is highest on streets as compared to trails; local roads had the highest volumes likely owing to the fact that all streets on the Virginia Tech campus are classified as local. Table 2 gives summary statistics for the AADT estimates used in spatial modeling.

3.2. Direct-demand model results

Our modeling approach offered 199 candidate variables for selection. Our final models included 5 variables for bicycle AADT and 6 variables for pedestrian AADT (Table 3). Bicycle AADT was positively correlated with aspects of the transportation network (centrality, on-street facilities, and major roads) as well as land use factors (population density). The fact that centrality was included in the models suggests that it is a useful tool for locating count sites in areas where counts do not exist; the centrality metric also takes into account infrastructure such as off-street trails which may explain why trails were not selected in the models despite having high levels of bicycle traffic. Household income was negatively correlated with bicycle traffic. This result is likely owing to the fact that high income neighborhoods are located in outlying areas of Blacksburg - often times in elevated locations (Blacksburg sits in a small valley) – which are heavily residential. The effect of income likely captures a combination of factors.

Similar to the bicycle model, pedestrian AADT was correlated with aspects of the transportation system (sidewalks, off-street trails, bus stops) and land use factors (household income, residential addresses, population density). Sidewalks, population density, and bus stops were positively correlated with pedestrian AADT; off-street trails, household income, and residential addresses were negatively correlated with pedestrian AADT. The finding that off-street trail traffic was negatively correlated with pedestrian AADT is likely a result of the fact that the highest pedestrian volumes occur on sidewalks near retail areas or the Virginia Tech campus which are often times on roads classified as local. Conversely, bicycle traffic was higher on off-street trails (Table 1) which is incorporated in the centrality variable in the bicycle model.

To allow for comparing coefficients among modes and variables with different units we fully normalized all regression coefficients. We multiplied each coefficient by this factor: difference between 95th and 5th percentile independent (e.g., land use) variable / difference between 95th and 5th percentile dependent (i.e., bike or pedestrian AADT) variable. The normalized coefficients are interpreted as the number of 95th/5th percentile interval increases of the dependent variable (bicycle or pedestrian AADT) for each 95th/5th interval increase in the predictor variable. There were commonalities among the models, for example, population density and household income were included in both models with the same direction of effect (i.e., traffic is higher in dense areas and lower in high-income, residential areas). However, nuances such as the difference in off-street trails and sensitivity to transit indicates that separate models are necessary to capture differences among modes. Additionally, there were a number of variables that were significant at a small spatial scale, mostly aspects of transportation infrastructure (major roads, on-street facilities, bus stops, off-street

Table 2
Summary statistics of AADT estimates at count locations by street functional class.

Road Type	Bicycle		Pedestrian	
	Count locations	Median (IQR[a]) AADT	Count locations	Median (IQR[a]) AADT
Major Road	29	28 (20–41)	24	192 (103–268)
Local Road	51	19 (7–36)	27	200 (109–603)
Off-street Trail	21	32 (12–118)	21	69 (19–102)

[a] IQR: Interquartile Range.

Table 3
Direct-demand model results for bicycle and pedestrian AADT in Blacksburg, VA.

Bicycle Model

Variable	Buffer	β	Normalized β[a]	p-value	VIF
HH Income	250	−8.8E-06	−0.0024	0.01	1.9
Centrality	–	2.8E-06	0.31	< 0.01	1.2
Major Roads	100	2.7E-03	0.12	0.01	1.1
Population Density	1,250	3.1E-04	0.27	< 0.01	1.7
On-Street Facility	100	3.6E-03	0.15	0.04	1.1
Intercept	–	2.5	–	< 0.01	–
		Adj-R^2	*0.52*	*N*	*101*

Pedestrian Model

Variable	Buffer	β	Normalized β[a]	p-value	VIF
Sidewalk	750	7.8E-05	0.47	< 0.01	2.1
Off-street Trail	100	−4.0E-03	−0.22	< 0.01	1.3
HH Income	1,750	−1.6E-05	−0.23	< 0.01	1.3
Residential Addresses	1,000	−6.2E-04	−0.23	< 0.01	1.5
Population Density	750	1.7E-04	0.16	0.01	1.5
Bus Stops	250	1.3E-01	0.14	0.03	1.5
Intercept	–	5.1	–	< 0.01	–
		Adj-R^2	*0.71*	*N*	*72*

[a] To compare model results among modes we fully normalized the coefficients for each regression model by multiplying each β by this factor: difference between 95th and 5th percentile independent variable/difference between 95th and 5th percentile dependent variable.

trails; ≤ 250 m buffer). This finding suggests that targeted improvements in infrastructure may have the ability to encourage cycling and walking. Other variables, such as population density (~1,000 m buffer), were included at large spatial scales and may need a more concerted, long-term effort to encourage active travel. Some variables, for example, length of sidewalks (750 m buffer), were significant at a medium-sized spatial scale suggesting that connectivity of the sidewalk network over neighborhood scales may be a better indicator of pedestrian traffic than the presence of a sidewalk at any given segment in the network.

3.3. Model validation

We explored model validity by goodness-of-fit, internal validation (i.e., scatterplots of observed vs. predicted values), and a Monte Carlo-based hold-out analysis. Our model goodness-of-fit was reasonable compared to previous models (Fagnant and Kockelman 2016; Hankey and Lindsey, 2016; Jones et al., 2010; Miranda-Moreno and Fernandes, 2011; Pulugurtha and Repaka, 2008; Schneider et al., 2009a, 2009b, 2012; Wang et al., 2016). However, our validation R^2 values (determined using the Monte Carlo-based hold-out analysis) showed a slight drop in model performance for the test as compared to the build data. This difference could be attributable to multiple factors, for example, we only had 101 (72) locations to model for bicycle (pedestrian) AADT. Removing 20% of locations for the Monte Carlo routine significantly reduces the sample size for model building; conversely, if a lower percentage of locations are removed as the "test" case, then there are few counts to validate the models. Alternatively, this result could mean our results are sensitive to the choice of count sites. Obtaining a larger number of count sites would help to better assess this issue. Fig. 2 shows results from both the internal and external (i.e., hold-out) validation procedures.

3.4. Spatial estimates of pedestrian and bicycle traffic at locations without counts

We mapped bicycle and pedestrian AADT estimates for all street and trail segments in Blacksburg (Fig. 3). Bicycle and pedestrian traffic demonstrated different spatial patterns underscoring the need to measure and model each mode separately. In general, bicycle traffic was highest on (1) off-street trails with access to the Virginia Tech campus or downtown Blacksburg and (2) corridors that had access to retail destinations. Pedestrian traffic was highest on the Virginia Tech campus and surrounding retail areas and diminished as distance from campus and downtown increased. In general, bicycle traffic was more dispersed throughout Blacksburg while pedestrian traffic was clustered near campus and retail locations. Overall, pedestrian traffic volumes were higher and more variable than bicycle traffic volumes.

4. Discussion

Our work aims to demonstrate how traffic monitoring programs can be designed for multiple objectives, for example, tracking performance measures and developing spatial models. Our study was completed in a small, rural community; however, our approach could potentially be scaled and employed in larger jurisdictions that already manage large count programs for motorized traffic.

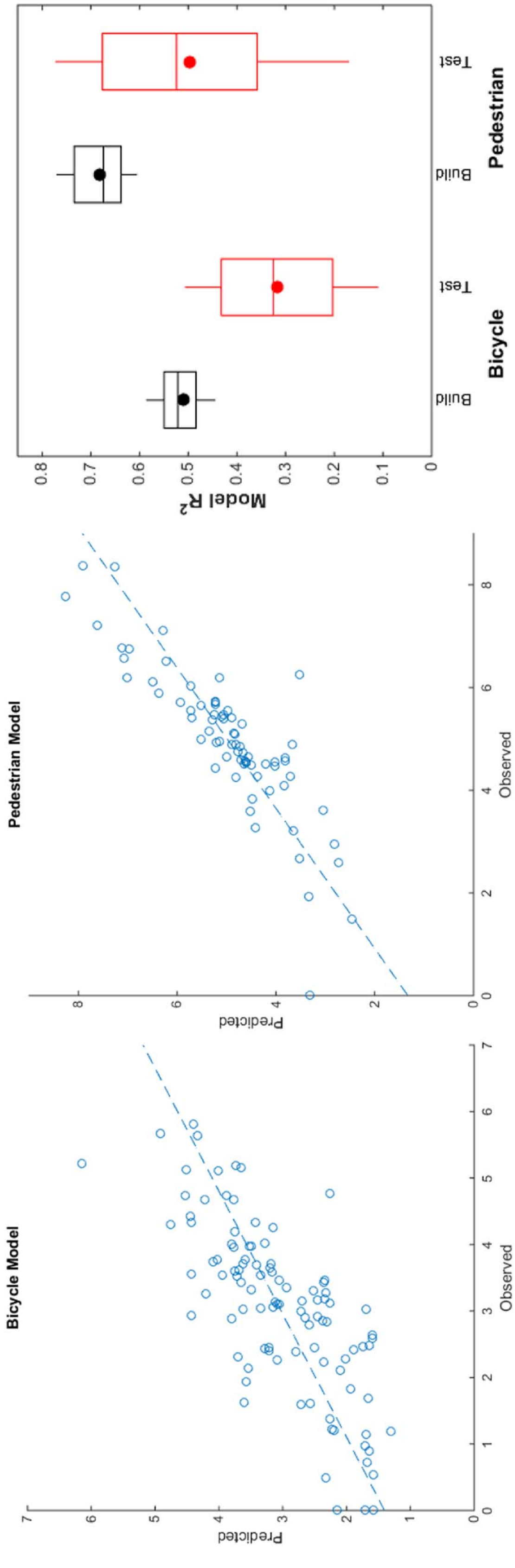

Fig. 2. Internal validation for the bicycle (left-panel) and pedestrian (middle-panel) models; Monte Carlo-based 20% hold-out analysis for each model (right-panel).

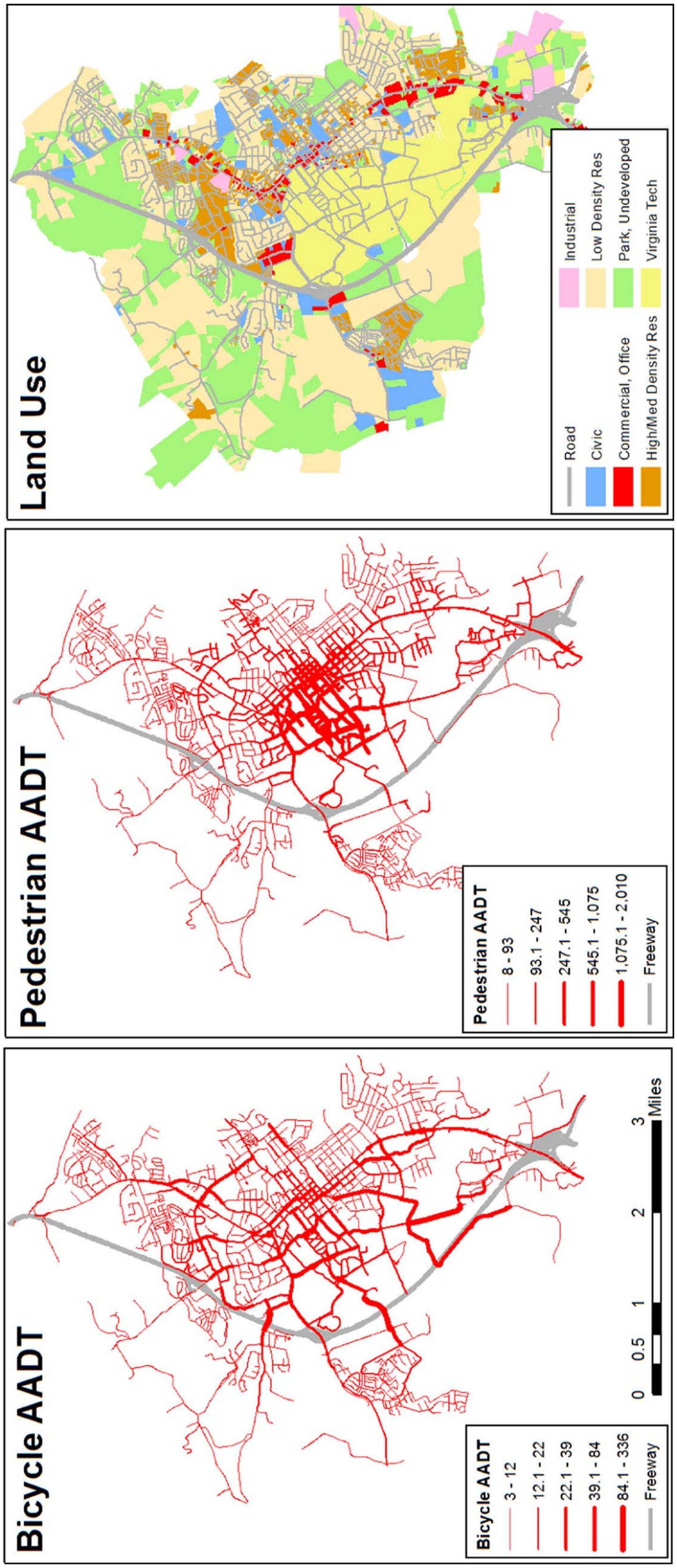

Fig. 3. Spatial estimates of bicycle and pedestrian AADT in Blacksburg, VA (left and middle panel); land use (right panel).

4.1. Implications for future research and exposure assessment

Our goal was to demonstrate how bicycle and pedestrian traffic monitoring efforts (with the primary goal of tracking performance measures) could be adapted to also develop spatial models that could be used for exposure assessment. Our traffic monitoring campaign was established to estimate AADT at specific locations to aid in planning decisions. We included in the traffic monitoring design (see Lu et al., 2017) locations that captured spatial variability of bicycle and pedestrian traffic and controlled for temporal differences using a combination of reference and short-duration count sites (following guidance by previous studies [Hankey et al., 2014; Nordback et al., 2013; Nosal et al., 2014]). Due to resource constraints we were only able to collect reference counts at 4 locations and short-duration counts at 97 locations. A useful extension of our work would be to site a larger number of both types of counts to better assess tradeoffs between number of count sites and model performance. Additionally, we were not able to collect pedestrian counts at locations where a sidewalk did not exist (i.e., mostly low density, residential locations); as such, we were not able to include these low volume locations in our model building. Finally, our study area represents a unique population in that it is a small college town and scaling our approach may encounter institutional (e.g., adapting existing count protocols for motor vehicles) and technological (e.g., counter accuracy) barriers; more work to test our approach in other areas would be beneficial.

An important use of the output of our spatial models is assessment of exposure to hazards. For example, our spatial surface of bicycle and pedestrian traffic could be used to calculate crash rates (rather than crash counts) across Blacksburg. Additionally, our models could be updated over time as new counts become available and new infrastructure is installed to better assess investments in infrastructure. By including spatial modeling as a criterion in the design of the traffic monitoring program, planners and engineers would have access to spatial estimates to monitor and track performance and exposure rates over time. This information could be included in decisions on how to allocate infrastructure spending.

4.2. Merging bicycle and pedestrian traffic monitoring and spatial modeling

A key goal of our work is to select count sites specifically for the purpose of spatial modeling; many previous studies use count datasets that are collected ad hoc over time (Fagnant and Kockelman 2016; Hankey and Lindsey, 2016; Jones et al., 2010; Miranda-Moreno and Fernandes, 2011; Pulugurtha and Repaka, 2008; Schneider et al., 2009a, 2009b, 2012; Wang et al., 2016). A difficulty associated with selecting sites to capture spatial variability is that many locations (such as Blacksburg) have little or no information on bicycle and pedestrian traffic levels to aid in the site selection process. We used a combination of street functional class and centrality to select sites; this approach seemed to work reasonably well for our study area. Given the information provided in our modeling work, a prudent decision may be to reassess count locations in future count campaigns (especially the reference site network) to ensure variability in traffic is captured over time. In order to achieve multiple objectives for traffic monitoring and spatial modeling, an iterative process may be beneficial depending on the local uses of the outputs of this process.

A benefit of using comprehensive traffic monitoring for model development is that temporally adjusted estimates of traffic patterns (i.e., AADT) are available for use in the models. To date, most direct-demand models use counts that are collected during varying hours of day and seasons. The use of temporally adjusted estimates gives greater confidence in the results of the spatial patterns that result as an output from the direct-demand models. Similarly, use of AADT allows for integrating bicycles and pedestrians into current decision frameworks that measure the same performance measures for motor vehicle traffic. By continuing to monitor and model AADT over time, transportation planners and engineers will be able to assess information for bicycles and pedestrians that is analogous to ongoing efforts for motor vehicles.

4.3. Monitoring in small communities and implications for other jurisdictions

Our models assess correlation between land use factors and rates of active travel. In general, our models are consistent with similar studies from larger urban areas. Specifically, population density was significant and positively correlated with bicycle and pedestrian traffic; transportation features such as bicycle facilities, bus stops, and sidewalks were also positively correlated with active travel. As with previous studies, we found that the spatial scale was not consistent among variables. For example, population density was significant at a large spatial scale (suggesting it may be necessary to establish policies that increase density as a long term goal) and infrastructure variables such as bus stops and bicycle facilities were significant at a small spatial scale (suggesting that targeted improvements in infrastructure may increase neighborhood-level rates of walking and cycling on relatively shorter time scales).

Resource inputs for our monitoring and modeling effort included capital costs for equipment (i.e., automated counters) and labor costs for installation and maintenance of the automated counters. Since the automated counters can be used repeatedly over time the ongoing costs of such a program would be reduced to labor inputs only in future iterations of counting. Our work serves as a proof-of-concept that count campaigns can be designed with spatial modeling in mind as a partial goal. Our work was carried out in a small community which allowed us to gather data on a representative number of segments in the network (~5.5%). Future efforts could test our approach in larger urban areas. Since the cost of implementing a program grows as the number of sites increases, long-term efforts might replicate common practices for motor vehicles such as rotating count sites on a 3-year basis and tabulating running averages of performance measures. This approach would then allow for spatial models to be developed on a semi-annual basis while removing the effects of seasonal and hourly traffic patterns.

In many cases it may be possible to slightly augment current data collection efforts to add information on cyclists and pedestrians. For example, we used pneumatic tubes (a common device used to count motor vehicles) to count cyclists on streets. We simply processed the data using an algorithm (provided by the manufacturer) that allows for counting cyclists as well as vehicles (see Lu et al., 2017 for details). Slight modifications to current data collection efforts may make it possible to include cyclists in ongoing, and extensive, motorized traffic monitoring campaigns.

Finally, our approach may have multiple practical uses in planning decisions for small and large communities. For example, Blacksburg is currently designing a plan for build out of the bicycle network. The spatial estimates of bicycle traffic from our models could be used to prioritize location of infrastructure on the network. Similarly, our counting and modeling approach could be repeated in subsequent years to measure change over time as new infrastructure is installed. Additionally, our spatial estimates of rates of active travel may be useful in exposure assessment. Outputs from our models (i.e., bicycle and pedestrian traffic volumes) could be used to calculate crash rates or exposure to environmental hazards (e.g., noise, air pollution).

5. Conclusions

We used results from a comprehensive bicycle and pedestrian traffic monitoring campaign to develop direct-demand models of bicycle and pedestrian AADT in Blacksburg, VA. We found that it was possible to design bicycle and pedestrian traffic monitoring programs that merge efforts to track performance measures and develop spatial models. In the absence of information on bicycle and pedestrian traffic patterns we found satisfactory results for site selection using a combination of street functional class and centrality (a measure of trip potential); this process resulted in a stratified sample of 5.5% of the network that was representative of the variability of traffic patterns across the Town. Our spatial models had reasonable goodness-of-fit (bicycle model R^2: 0.52; pedestrian model R^2: 0.71) and produced spatial estimates for all street and trail segments in Blacksburg. Results from these spatial models could be used to track performance measures over time, measure impacts of infrastructure installation, assess exposure to hazards, and estimate benefits from active travel. Our work serves as a proof-of-concept in a small, rural college town to merge goals of traffic monitoring programs and spatial modeling; however, our approach could potentially be scaled in other jurisdictions (or ongoing motorized traffic monitoring campaigns could be adapted) to acquire similar outputs.

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