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

Tianjun Lu[a], Andrew Mondschein[b], Ralph Buehler[c], Steve Hankey[a,*]

[a] Virginia Tech, 140 Otey Street, Blacksburg, VA 24061, USA
[b] University of Virginia, Campbell Hall, PO Box 400122, Charlottesville, VA 22904, USA
[c] Virginia Tech, 1021 Prince Street, Alexandria, VA 22314, USA

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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

* Corresponding author.
E-mail address: hankey@vt.edu (S. Hankey).

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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.