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Neighborhood Correlates of Urban Trail Use

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Purpose: To model urban trail traffic as a function of neighborhood characteristics and other factors including weather and day of week. *Methods:* We used infrared monitors to measure traffic at 30 locations on five trails for periods ranging from 12 months to more than 4 y. We measured neighborhood characteristics using geographic information systems, satellite imagery, and US Census and other secondary data. We used multiple regression techniques to model daily traffic. *Results:* The statistical model explains approximately 80% of the variation in trail traffic. Trail traffic correlates positively and significantly with income, neighborhood population density, education, percent of neighborhood in commercial use, vegetative health, area of land in parking, and mean length of street segments in access networks. Trail traffic correlates negatively and significantly with the percentage of neighborhood residents in age groups greater than 64 and less than 5. *Conclusions:* Trail traffic is significantly correlated with neighborhood characteristics. Health officials can use these findings to influence the design and location of trails and to maximize opportunities for increases in physical activity.

Key Words: trail use, neighborhood, urban form, physical activity

Experts in health, planning, transportation, and recreation are collaborating in studies of the effects of urban form on physical activity, including the relationship between physical activity and multiuse trails built for recreation, fitness, transportation, and other utilitarian purposes. Few objective measures of trail use are available, and experts in all fields agree that research is needed to determine factors that affect trail use. In the transportation literature, models for forecasting pedestrian traffic exist, but many studies have reported results based only on non-random samples that cannot be generalized.[1-6] Experts consider the quality of existing measures "poor" and the priority for additional data to be "high."[5] The recreation literature includes studies that characterize users and activity patterns through user-intercept surveys and other methods, but data about use of facilities have not been collected systematically, standardized measures have not been developed, and models for estimating trail traffic generally have not been reported.[7-13] Planners and health researchers have begun to report findings that indicate particular features of urban form may influence physical activity, and there is preliminary evidence that prox-

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imity to trails may increase physical activity.[14-22] Additional research is needed to confirm these findings, identify characteristics of neighborhoods that correlate with trail use, and specify consistent, objective measures of these characteristics. The objectives in this paper are to present new objective measures of trail traffic, additional evidence on covariates of trail use, and a model that can be used for forecasting traffic on existing or proposed trails.

Methods

Trail Traffic Counts

We present here measures of urban trail traffic from what is believed to be the most comprehensive and longest-running trail monitoring network in the US. We monitored trail traffic 24 h per day, 7 d per week at 30 locations on five multiuse greenway trails in Indianapolis using Trailmaster infrared monitors (Figure 1). Monitors were located approximately 1 mile apart to provide coverage of a 33-mile trail network, with adjustments to reflect barriers such as arterial crossings. The dataset includes results from monitoring at four locations on one trail from February, 2001 through July, 2005; two locations on a second trail between June, 2002 and July, 2005; and 24 locations on five trails between May, 2004 and July, 2005.

The monitors record the time when an infrared beam from a transmitter to a receiver is broken by a user on the trail; each time the beam is broken is one individual count. The time the beam must be interrupted to register an event can be adjusted, and the monitors have been recalibrated periodically. The counts reflect total traffic, or users past a point on a trail, not numbers of different users, and they do not distinguish among types of users. The monitors systematically underestimate total traffic because they may record only one count when two or more users pass simultaneously. To adjust for this error, and to take into account recalibration of the monitors, we periodically conducted field observations to develop correction equations. For example, during June and July, 2004, after expansion of the monitoring network in May 2004, we developed hourly correction equations from 442 h of observations at 28 locations. Observers recorded information manually in 5-min intervals between 7:00 AM and 7:00 PM, including total traffic, mode of trail use (walking, running, skating, cycling, or other activity), gender, number of groups, and people per group. We totaled counts by hour and, controlling for level of traffic, regressed observed traffic on estimates from the monitors. The correction equation is ($r^2 = 0.99$):

Estimated actual use = (–0.0205 + X + 1.04563*Sqrt (monitor count))^2
where

$X = 0$	if $0 <$ monitor count ≤ 60
$X = 0.2287$	if $60 <$ monitor count ≤ 110
$X = 0.3938$	if $110 <$ monitor count ≤ 200
$X = 0.4551$	if monitor count > 200

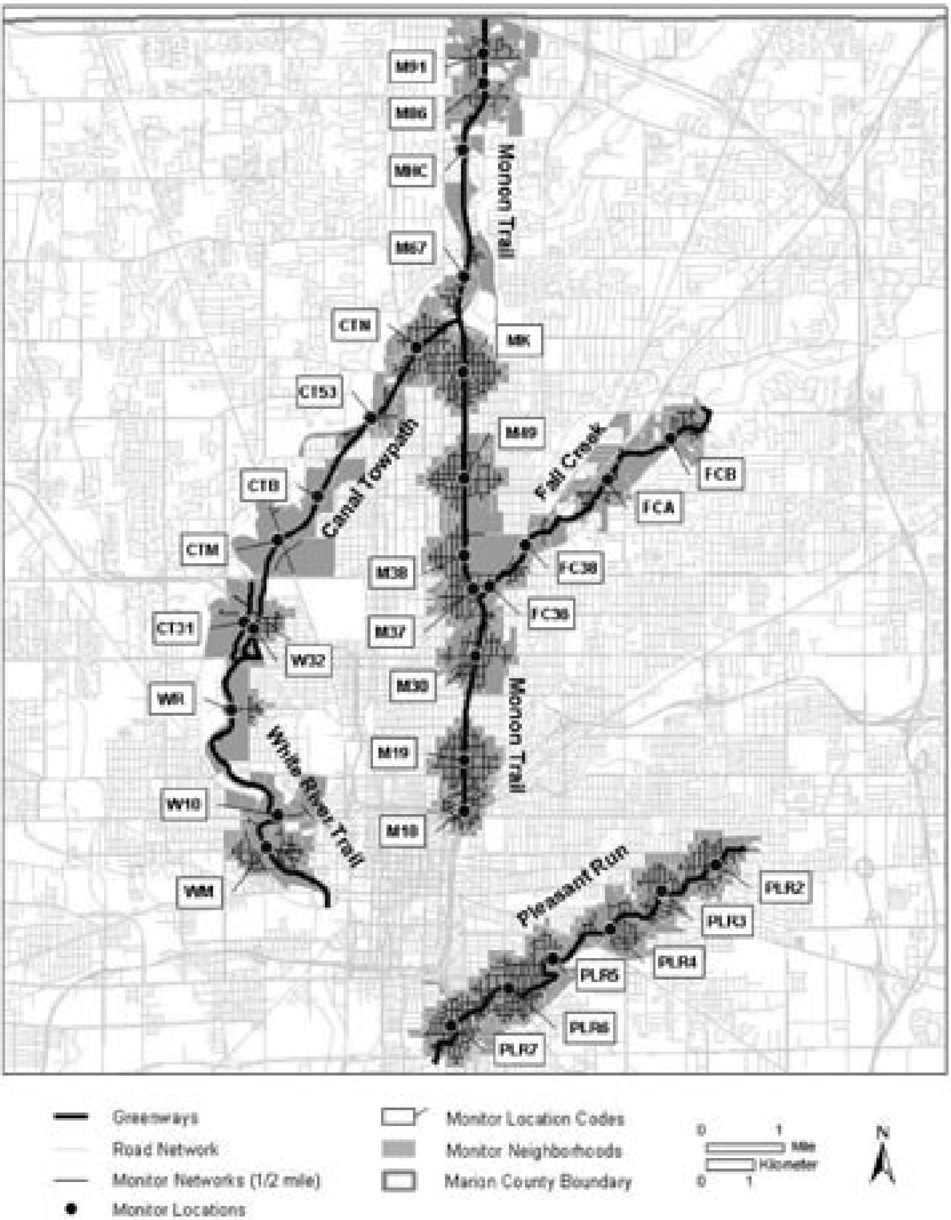

Figure 1—Map of trail monitoring locations, Indianapolis, Indiana

This equation is used to estimate hourly traffic from all counts between May, 2004 and July, 2005. Similar equations were estimated in similar ways for earlier time periods.

After hourly counts were corrected, they were aggregated to daily counts for the monitoring period. Since the dates the monitors were installed, 19,581 d of counts potentially are available. Counts are available for 18,142 (93%) of the possible days; counts for 7% were lost due to counter malfunction, vandalism, infestation by insects, or human error. The daily counts are the dependent variable in the models presented herein.

Measures of Urban Form and Neighborhood Characteristics

Measures of urban form and neighborhood characteristics were developed using geographic information systems (GIS), satellite imagery, and demographic data from the US Bureau of the Census. Measures were estimated for neighborhoods around each monitor location, which may be considered pedestrian access zones or catchment areas. Mean values for measures for these neighborhoods are presented in Table 1.

Monitor Locations. Geographic coordinates for monitor locations were determined using a global positioning system (GPS) receiver and PDA device equipped with mobile GIS software (ArcPad). GPS readings were collected at 2 s intervals for a minimum of 1 min at each monitor location. The GPS coordinates were transformed into a GIS point layer and the mean center of the readings at each location was calculated by averaging the X and Y values. These points were overlaid on 6-inch resolution orthorectified color aerial photography and a vector GIS representation of the greenways to provide a visual check of accuracy. Where necessary, point locations were manually adjusted, using the aerial photography so that each point intersected the closest trail segment.

Trail Monitor Neighborhoods. To determine boundaries of monitor neighborhoods, road features were extracted from 2000 Census TIGER data and intersected with greenway vectors to create a network mobility model. Network modeling routines in Arc/Info were applied to delineate trail and road segments within ½ mile distances from each monitoring point. Census blocks that intersected or were adjacent to these ½ mile network segments were selected to define the neighborhood for each monitoring location. Although the street network layers from the TIGER database are not as accurate as other GIS street network layers, they were used because they align more precisely with census block boundaries. Physical and socioeconomic characteristics were summarized for individual blocks in these neighborhoods. Because income and education data are available only for census block groups, individual blocks were assigned the same value as the block group in which they were located. This procedure reflects the assumption that the variability among blocks and block groups within the trail monitor neighborhoods is not sufficient to have any impact on the model.

Neighborhood Socio-demographic Characteristics. Socio-demographic variables included income, education, age, and race. Income was defined as the average median household income for census block groups. Educational attainment

Table 1 Variables in Trail Traffic Models

Independent variables	Mean	Units/notes	Hypothesized effect
Temporal variables			
weekend	0.2875	Dummy variable, 1 if weekend day, 0 otherwise	positive
Jan	0.0728	Dummy variable, 1 if Jan, 0 otherwise	no difference (relative to December)
Feb	0.0718	Dummy variable, 1 if Feb, 0 otherwise	positive
Mar	0.0804	Dummy variable, 1 if Mar, 0 otherwise	positive
Apr	0.0842	Dummy variable, 1 if Apr, 0 otherwise	positive
May	0.1124	Dummy variable, 1 if May, 0 otherwise	positive
Jun	0.1088	Dummy variable, 1 if Jun, 0 otherwise	positive
Jul	0.1156	Dummy variable, 1 if Jul, 0 otherwise	positive
Aug	0.0681	Dummy variable, 1 if Aug, 0 otherwise	positive
Sep	0.0700	Dummy variable, 1 if Sep, 0 otherwise	positive
Oct	0.0727	Dummy variable, 1 if Oct, 0 otherwise	positive
Nov	0.0704	Dummy variable, 1 if Dec, 0 otherwise	positive
Aug-38thSt	0.0063	Dummy variable, 1 if State Fair in session, 0 otherwise	positive
Weather variables			
TempDev	1.3121	Deviation of daily average temperature from normal, in deg. Fahrenheit	positive
PrecipDev	0.0186	Deviation of daily precipitation accumulation from normal, in inches	negative
SnowDev	-0.0027	Deviation of daily snow accumulation from normal, in inches	negative
SunDev	-0.9827	Deviation of daily percentage sunshine from normal	positive
Socio-demographic variables			
YoungOld%	18.07	Percentage population less than 5 and greater than 64	negative
Black%	39.67	Percentage African American	negative
Other%	4.56	Percentage other ethnicity, exclude white and African American	negative
College25Ave%	33.29	Mean percentage population 25+ with college degree	positive
MHHIncAve	40010.6	Mean of median household incomes, in dollars	positive
Urban form variables			
NDVI_Ave	0.1350	Mean NDVI value in census blocks 1/2 mile from counter on 06/06/00	positive
PopDensity	1119.8	Population density per square kilometer in 1/2 mile network distance to monitor	positive
Commercial%	5.2263	Percentage of commercial land use in trail neighborhood	positive
PrkLotArea	31	Parking lots (sq. ft.) in trail neighborhood	positive
StreetLngth	431.17	Average length of network street segments within 1/2 mile of counter	negative

was defined as the percent of adults over age 25 with a college degree. An age variable, YoungOld%, was defined as the sum of the percentages of population less than age 5 and greater than age 64. Three race variables were defined: percent white, percent black, and percent other race. Ethnicity, including Hispanic, was not analyzed separately.

Measures of Urban Form and the Environment. Measures of urban form and the physical environment were estimated from internal data and spatial data from local government agencies. Population density is considered a dimension of urban form because density is a policy variable that can be manipulated through zoning and other regulatory or programmatic decisions. Gross population density was computed from population estimates in census block data. Gross rather than net population density (based only on residential land use) was used because it better reflects the distribution of people in the areas defined by the ½ mile street segments.

Parcel-level data compiled by the City of Indianapolis were used to determine the land use mix within monitor neighborhoods. Detailed land use categories were aggregated into fewer categories, including residential, commercial, industrial, special use, park, water, parking lot, and transportation. Commercial land use includes office, retail, and heavy commercial. These categories were combined because each includes potential destinations that could affect decisions by people to use a trail. Additional urban form variables were derived from the street networks used to define monitor neighborhoods. Network segment average length is analyzed because theory suggests that shorter block lengths facilitate accessibility and pedestrian activity.

Previous research on the interaction between vegetative characteristics of the physical environment and human health indicates that exposure to green landscapes positively influences a variety of human psychological and physiological processes[23,24] and that humans have preferences for healthy green landscapes.[25-27] Vegetative characteristics in monitor neighborhoods were measured using biophysical remote sensing techniques and multispectral imagery acquired by the Landsat Thematic Mapper Plus (ETM+) remote sensing system. The normalized difference vegetation index (NDVI) serves as a measure of greenness. Measures come from four dates that capture vegetation phenology from early spring through mid-summer: April 12, 2003; May 8, 2001; June 6, 2000, and July 11, 2001. Imagery was selected from multiple years to provide the best quality in terms of minimum cloud cover and atmospheric haze. NDVI is computed with a well-established algorithm that uses reflectance measurements in the red and near infrared (NIR) portions of the electromagnetic spectrum to estimate vegetation characteristics (NDVI = NIR – red / NIR + red).[28] NDVI is unitless and takes on values from within the range of –1 to +1 where higher values are indicative of increasing vegetation density and health and lower values are indicative of stressed vegetation or non-vegetated landscapes. Numerous studies have shown that NDVI values correlate significantly with biophysical vegetation characteristics including green biomass, leaf area index, and percent vegetated ground.[29-31]

Temporal and Weather Variables. To control for seasonal and day-of-week effects on trail use, dummy variables for months and for weekend days were defined. To control for the effects of variations in daily weather, long-term average daily measurements from the National Oceanic and Atmospheric Administration were used to define a set of weather variables that were computed as deviation from the long-term daily mean.[32] For each day in the database, temperature deviation was measured as the difference between the average recorded temperature and the long term daily average for that day (in degrees Fahrenheit). Measures for precipitation and snow were computed similarly and measured in inches. Sunshine was measured in percent of hours in the day.

Modeling Approach and Regression Techniques

Multiple regression techniques were used to model daily trail traffic as a function of day-of-week, month, weather, and trail neighborhood characteristics, including socio-demographic characteristics and urban form. Conceptually, the probability that an individual in a neighborhood uses a particular trail segment and is counted by a monitor is a function of the person's preferences, the characteristics of the neighborhood around their home, the distance to and other characteristics of alternative routes to a trail access point, the characteristics of the access point, and the characteristics of the trail segment and its contiguous neighborhood. This conceptual model cannot be estimated, however, because data from individuals about their trail use are not available. Instead, traffic was modeled as a function of trail monitor neighborhoods and control variables to make inferences about factors that correlate with trail use. The dependent variable, daily trail traffic, is log-transformed prior to estimation of the model. The hypothesized effect of each independent variable is presented in Table 1. The model initially was estimated using a step-wise process; theoretically important variables were retained in the model even if not significant. Multicollinearity was analyzed and addressed using the variance inflation factor and with orthogonalization procedures in SAS.

Results

Descriptive results include information about traffic patterns on trails, including activity patterns and user characteristics from field observations and measures of temporal and spatial variation in trail traffic. The regression model identifies significant covariates of trail use that have implications for policy and management.

Activity Patterns and User Characteristics

Cycling was the predominant activity observed on each of the five trails, accounting for 46% to 61% of users (Table 2). Walkers ranged from 19% to 39% of observed users and outnumbered runners on all but one trail. The percentage of runners ranged from 5% to 23%. Skaters never exceeded more than 7% of users, and no skaters were observed on two trails, one of which has a gravel surface that is unsuitable for skating.

Users were disproportionately male: across the five trails, females accounted for 25% to 44% of observed users. Observers categorized approximately 58% to 93% of users as white, 6% to 37% as black, and smaller proportions as other. The percentage of users in groups of two or more ranged from 30% to 40%.

Table 2 Observed Trail Traffic and User Characteristics*

	Monon	White River	Canal Towpath	Fall Creek	Pleasant Run	Total
Trail traffic						
Mean hourly count	71.6	8.7	11.5	5.4	3.4	42.6
Activity type (percent of users)						
Cycle	61	55	55	46	48	60
Walk	19	22	20	39	37	19
Run	11	21	23	11	5	11
Skate	7	1	0	0	5	6
Other	3	0	2	5	5	2
Gender (percent of users)						
Male	57	75	56	59	73	58
Female	43	25	44	41	27	42
Ethnicity (percent of users)						
White	87	84	93	58	80	83
African American	11	12	6	37	15	14
Other	2	3	2	5	5	3
Group usage (percent of users)						
Users in groups	40	31	33	30	40	36

Note. *Observations taken for 442 hours across 28 locations on five trails.

Temporal and Spatial Variation in Trail Use

Trail use varies significantly by hour of day, day of week, month of year, across different trails, and across trail segments or locations on individual trails. These illustrative results have implications both for modeling and for policy and management.

Temporal Variation in Trail Use. Figure 2 presents daily use and mean weekday and weekend daily use by month for 2004 at the location which historically has had the highest traffic. The graph illustrates both the seasonality of trail use and the magnitude by which weekend use exceeds weekday use by month. Daily traffic ranged from 52 to 6155. For the year, the mean daily traffic was 87% higher on weekend days (2553) than on weekdays (1360).

Figure 3 presents mean daily traffic by day of week for the same location for a 4-y period (2001-2004). Although variation exists, Sunday traffic generally has been higher than Saturday traffic, and traffic generally has declined slightly from Monday through Friday. There have been no significant increases or decreases in traffic during the past 4 y.

Figure 4 presents monthly traffic at four locations (including the location in Figures 1 and 2) within a 3.3 mile segment of the same trail for a 1-y period. Traffic was significantly different across locations, ranging from 2277 in December near 38th Street to 86,254 in July near 67th Street. The spike in use near 38th Street in August reflects traffic associated with the Indiana State Fair, which is adjacent to the monitoring location.

Figure 5 presents mean hourly traffic for weekday and weekend days at locations on the White River and Monon Trails. At both locations, hourly traffic patterns on weekdays are different than weekend patterns. The weekdays are characterized by late-afternoon and early evening peaks, although, on the White River Trail, there also is a mid-afternoon peak. On weekend days, trail use rises somewhat later in the day and maintains a relatively high, constant rate until late afternoon when use decreases. Use of the White River Trail, which is adjacent to a university campus, extends later into the evening.

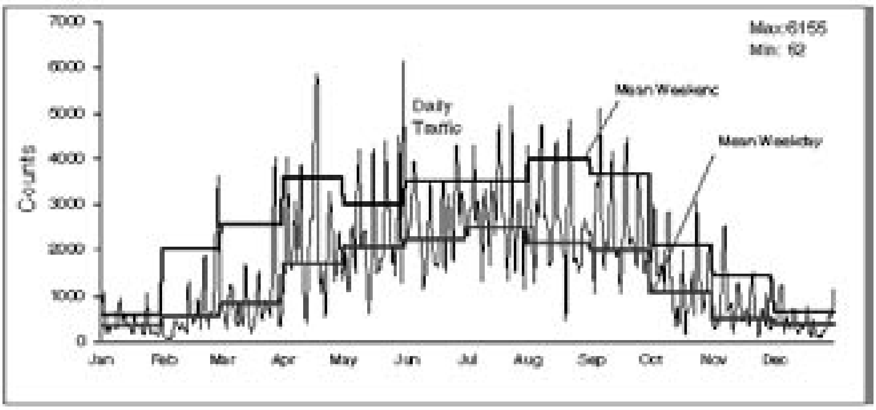

Figure 2—Variation in daily traffic, Monon Trail near 67th Street (M67), 2004

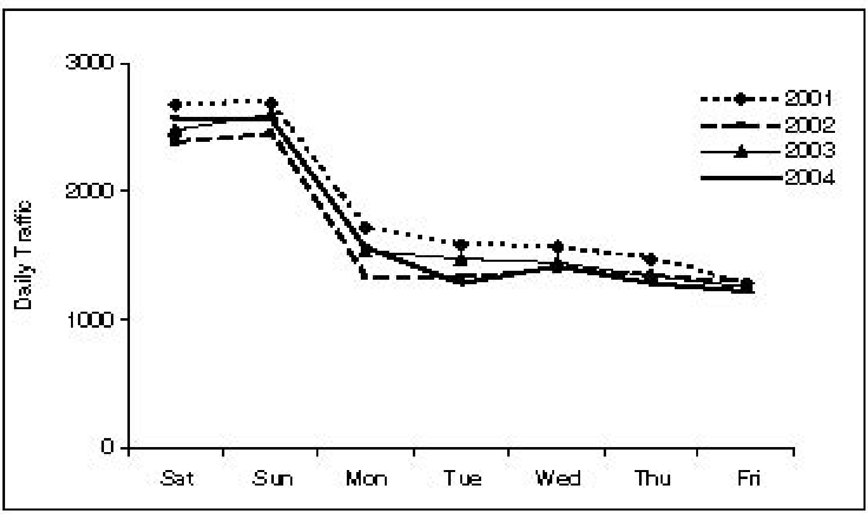

Figure 3—Variation in mean daily traffic, Monon Trail near 67th Street, 2001-2004*

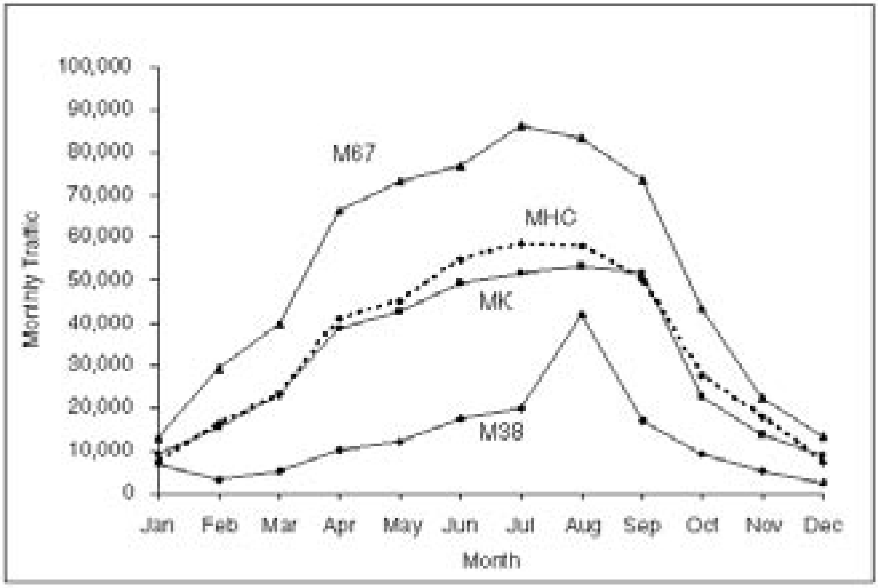

Figure 4—Variation in monthly traffic at four locations on Monon Trail, 2004*
*Codes correspond to counter locations in Figure 1 (e.g., M = Monon Trail; 67=67th Street).

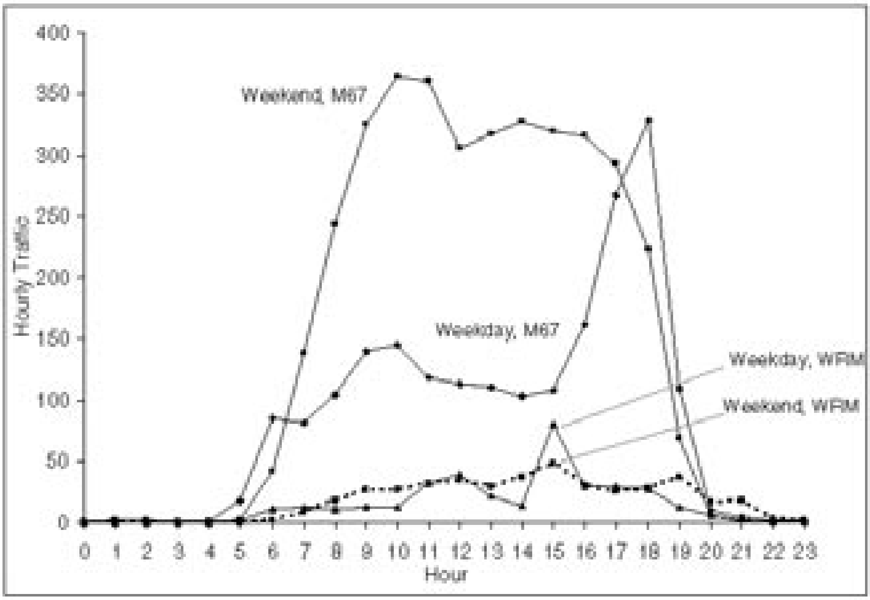

Figure 5—Variation in mean hourly traffic, Monon (M67) and White River (WRM) Trails, September 2004*
*Codes correspond to counter locations in Figure 1 (e.g., M = Monon Trail; 67=67th Street).

Patterns illustrated in Figures 2 through 5 generally are consistent and illustrative of patterns at other monitoring locations. During September 2004, mean weekend daily traffic ranged from 105 to 3670 across the 30 locations; the mean counts for weekdays ranged from 79 to 2017. Six locations had mean weekend daily counts greater than 1000; all were on continuous, connecting segments of the same trail. Differences in traffic levels reflect variations in both trail and neighborhood characteristics.

Trail Traffic Model

Table 3 presents the estimated model of daily trail traffic. The model explains approximately 80% of the variation in trail traffic. Most of the variables have associations in the expected directions, and all of the 29 variables are statistically significant.

Temporal and Weather Variables. The weekend variable and each of the monthly dummy variables are positive and significant. Although average monthly temperatures in Indianapolis are lower in January and February than December, average daily trail traffic is greater. Possible explanations may be that days are shorter in December, fewer people exercise because of the holiday season, more people initiate exercise in January, or, in anticipation of spring, people respond more to fluctuations in weather conditions in February. All other factors equal, the data indicate that weekend daily traffic is on average approximately 1.5 times weekday daily traffic. If the temporal variables are omitted from the regression equation, the Adjusted R^2 drops to approximately 0.60, indicating that these variables explain 20% of the variation in daily trail traffic.

Each of the weather variables is significant and has the expected effect. Deviations in average temperatures above the daily mean and greater percentages of daylight hours with sunshine increase trail traffic significantly, while increases in precipitation above average significantly decrease trail traffic. For example, other factors equal, an increase in daily mean temperature of one degree Fahrenheit above the long-term mean will increase traffic approximately 3.2%. The reversal of signs on the coefficients for the first order and squared temperature deviation terms indicates that the effects of large deviations from normal (i.e., above-average temperatures) diminish and may be negative when deviations become very large. For example, on very hot summer days, temperatures well above average may be a deterrent to outdoor physical activity. Precipitation always reduces traffic: holding other factors equal, an inch of precipitation above average will reduce traffic by approximately 40%. If only the weather variables are omitted from the regression equation, the Adjusted R^2 drops to approximately 0.74.

Socio-demographic Variables. Daily trail traffic is positively and significantly correlated with the percentage of adult residents older than 25 with college degrees and with neighborhood median household income. As indicated by the squared income term, however, the relationship between neighborhood income and trail use is nonlinear: the effects of income diminish as income increases. The age variable (YoungOld%) is negative and significant, indicating that daily trail use is lower in trail neighborhoods with greater proportions of residents either younger than 5 or older than 65. For every percentage increase in the population over 25 with

Table 3 A Model of Trail Traffic

	Parameter estimate	t value	Pr > |t|
Intercept	–43.6463	–7.38	< 0.0001
Temporal variables			
Weekend	0.4183	39.38	< 0.0001
Jan	0.1319	5.29	< 0.0001
Feb	0.4336	17.49	< 0.0001
Mar	0.8837	36.20	< 0.0001
Apr	1.4536	60.51	< 0.0001
May	1.6099	70.40	< 0.0001
Jun	1.8723	79.76	< 0.0001
Jul	2.0185	86.91	< 0.0001
Aug	2.0733	78.22	< 0.0001
Sep	1.8247	71.32	< 0.0001
Oct	1.3193	52.13	< 0.0001
Nov	0.7477	29.21	< 0.0001
Aug–38	0.6228	9.92	< 0.0001
Weather variables			
TempDev	0.0322	51.63	< 0.0001
$TempDev^2$	–0.0006	–13.38	< 0.0001
PrecipDev	–0.3999	–30.46	< 0.0001
SnowDev	–0.0509	–4.48	< 0.0001
SunDev	0.0066	42.58	< 0.0001
Demographic variables			
College25Ave%	0.0636	71.34	< 0.0001
MHHIncAve	9.5799	8.30	< 0.0001
$MHHIncAve^2$	–0.5111	–9.06	< 0.0001
YoungOld%	–0.0196	–14.58	< 0.0001
Black%	0.0099	39.51	< 0.0001
Other%	0.0178	9.96	< 0.0001
Urban form variables			
NDVI_Ave	1.1988	9.36	< 0.0001
PopDensity	0.0002	18.69	< 0.0001
Commercial%	0.0465	23.56	< 0.0001
PrkLotArea	0.0346	16.02	< 0.0001
StreetLngth	0.1172	6.27	< 0.0001

Note. Dependent Variable: Natural Log of Daily Counts (n = 18,142); Adj. R^2 = 0.7966; F = 2446 a college degree, an increase of 6.4% in daily trail traffic can be expected. Conversely, for every percentage increase in the young-old age categories, trail traffic can be expected to decrease 2%. Similar to the effects of deviations from average temperature, the sign on the mean median household income coefficient is positive, while the sign on the squared income term is negative. This result indicates that the effects of income diminish in higher ranges. A possible explanation is that households with higher incomes have more substitutes for use of trails.

The neighborhood ethnicity variables, Black% and Other%, both are significant and have positive signs. These variables are interpreted relative to the percentage of white residents in neighborhoods. They indicate trail traffic is higher in neighborhoods where there are higher percentages of minority residents relative to whites. This result is interesting given that field observations indicate that whites account for a disproportionate proportion of users. If the six socio-demographic variables are omitted from the regression, the Adjusted R^2 drops to approximately 0.56.

Urban Form Variables. Daily trail traffic is positively and significantly correlated with increases in population density, greenness (i.e., mean NDVI), the percentage of trail neighborhood in commercial use, the area in trail neighborhoods in parking lots, and the mean length of street segment**.** An increase in population density in trail neighborhoods of 100 persons per square kilometer, for example, is associated with an increase in trail traffic of nearly 2%. Every 1% increase in the area of parking lots is correlated with an increase in traffic of less than one-tenth of a percent (0.035%). A 1% increase in the length of the mean street segment length is associated with an increase in trail traffic of 0.117%. This correlation is inconsistent with design theory which hypothesizes that shorter block lengths may facilitate pedestrian activity. If the urban form variables are omitted from the regression, the Adjusted R^2 drops only about 1% to 0.79.

Discussion

We have presented measures of urban trail traffic derived from data collected from 30 infrared monitors on a five trail, 33-mile network over periods of up to 4 y. The results add to previous findings on trail use by establishing several socioeconomic and urban form variables as significant correlates of trail use. These results inform planners, heath researchers, and others interested in the relationship between physical activity and the built environment.

Objective Measures of Trail Traffic

These results demonstrate that trail traffic varies significantly over space and time, including over segments of individual trails. Trails in Indianapolis appear to be used predominantly for cycling, at least in summer, and proportions of walkers generally exceed runners. Based on field observations, users are disproportionately male and, relative to the city population as a whole, disproportionately white. Trail use appears to be a social activity for many users: 30% to 40% were observed in groups of two or more.

Analyses of data from infrared monitors show that trail use varies systematically by time of day, day of week, and month, but not from year to year. At most locations on weekdays, peaks occurred after work hours, although small morning peaks, mid-afternoon peaks, and peaks at other times also were observed. Regardless of location, weekend daily use was higher than weekday daily use, although it typically began later in the day and declined earlier. Variations in traffic throughout the year show clearly that trail use is a seasonal activity for many users. Data from four locations over 4 y indicate that no significant changes in trail traffic occurred. Traffic levels varied significantly across the five trails and at locations short distances apart on the same trail. These results maintained over time: particular segments of particular trails consistently received greater use.

Observers in the field did not attempt to distinguish between utilitarian and other users. However, the periods and locations of peak traffic likely reflect use of the trails for fitness and recreation, not commuting or utilitarian purposes. This inference is made because morning weekday peaks do not correspond in magnitude to peaks observed for late afternoons and early evening. The smaller peaks observed on weekdays before the beginning of the work day may indicate either commuting or use for fitness-related physical activity.

Evidence on Covariates of Trail Use

Possible explanations for the observed variations in traffic are that some segments are proximate or accessible to more users, that people in particular neighborhoods are more likely to use trails, or that people who use trails have preferences for segments in particular neighborhoods with particular characteristics and are willing to travel to them. These explanations cannot be analyzed directly because data from individuals about their trail use, preferences, and other behaviors are not available, but the forecasting model provides insights into covariates of trail use.

After controlling for day of week, monthly, and weather-related effects, it was shown that trail traffic is correlated with measures of socioeconomic status (i.e., household income and educational attainment) in trail monitor neighborhoods. Possible interpretations are that individuals with higher status are more likely to use trails or that individuals prefer to use trails in neighborhoods inhabited by wealthier, better educated people. Trail traffic is lower in neighborhoods where there are higher proportions of the young and old who may be less likely to use trails. These results also indicate that trail traffic is positively and significantly correlated with the proportion of minority residents in a trail monitor neighborhood. However, this result cannot be interpreted as evidence that minorities are more likely to use trails, especially given the findings from field observations which indicate that whites are over-represented relative to the city population as a whole. Information from household and user surveys is needed to resolve questions related to the effects of socio-economic status and race on trail use. It is likely that these factors affect both an individual's likelihood of trail use and his or her choice of particular neighborhoods and trail segments for use.

From policy and managerial perspectives, the most important findings concern the correlation between trail traffic and measures of urban form and the physical environment estimated for trail monitor neighborhoods or pedestrian access zones. These findings are important because decision-makers can manipulate them through policy choices such as zoning or through investment decisions. All other factors equal, trail traffic is greater in neighborhoods with greater population density. This finding is supportive of arguments in the planning literature that increases in population density can increase efficiency in utilization of public facilities and infrastructure.[15, 33] It also is consistent with findings in the health literature which suggest that proximity to trails increases likelihood of physical activity.[17, 18]

Planning theorists hypothesize that mixed land uses may encourage pedestrian activity.[15, 33] These results, which indicate that trail traffic is higher in neighborhoods with greater proportions of commercial land use, constitute evidence in support of this hypothesis. People may be using trails to access commercial areas and other destinations or in conjunction with other activities in mixed use areas. The significance of the StateFair variable reflects the fact that traffic on the adjacent segment of the Monon Trail is significantly greater on days when the fair is in session. The general implication is that trail use may be higher on days when trails can be used to access destinations or events.

It is known that many users drive to trails to use them.[34, 35] The model indicates that trail traffic is positively correlated with the area of parking lots within trail monitor neighborhoods. This finding suggests that the availability of parking may be an important component of accessibility. Because the amount of parking may be correlated with the amount of commercial land use, this result also may indicate the importance of the proximity of utilitarian or other destinations for trail use.

Planners and others have argued that planting trees in cities provides numerous benefits.[36, 37] Trail traffic is positively correlated with NDVI, a well-established index of vegetative density and health. This finding is important from a managerial perspective because the distribution of vegetation is one dimension of urban form that can be manipulated in comparatively short time frames.

The finding that trail traffic is correlated positively with mean street segment length is inconsistent with theory. Additional research to explore the relationship between trail traffic and street segment length is warranted.

Model for Estimating Trail Traffic

Planners and others in Indianapolis can use this model to estimate traffic at locations on existing or proposed trails. For example, on September 12, 2005, at the 67th Street location on the Monon Trail, the model predicts daily traffic to be 1982; actual traffic was 2136, a difference of 7.8%. Although additional validation studies are warranted, this result indicates that the model has potential application in forecasting applications. Forecasts may be used in feasibility studies for new trails, to assess the need for safety features such as stop lights at street intersections, or to design protocols for sampling users. However, because cities in different regions have different climatic regimes, sociodemographic characteristics, and urban form, research to extend, test, and validate the model must be completed before it may be used elsewhere.

Implications for Research, Policy, and Management

These findings can be used to inform and design research projects as well as interventions to increase physical activity. Researchers can use the results to design efficient sampling strategies that take into account spatial and temporal variation in use. For example, a common approach to surveying trail users is to intercept users on trails or at access points. Researchers can use these results to estimate numbers of users at locations and to design protocols for surveys.

Planners in urban places across the US are engaged in debates over reform of zoning regulations and redevelopment strategies in urban neighborhoods. The results constitute additional evidence in support of some of the principles of smart growth and new urbanism. Transportation and recreation planners responsible for review or funding of alternative trail projects can use our results to inform assessments of their relative feasibility or to develop inputs into benefit-cost analyses undertaken to optimize allocation of resources.

From a health perspective, these results provide important contextual information for specialists responsible for designing interventions to increase physical activity. Understanding variations in time-of-day and seasonal use can inform design of exercise regimes, while understanding of spatial variations in use can inform decisions about where programs are needed. The fact that more than one-third of users were observed in pairs or larger groups has implications for design of educational and marketing campaigns related to trail use.

Need for Additional Measures and Research

This research includes analyses of traffic counts and field observations of trail users and identifies correlates of trail traffic in trail monitor neighborhoods. An individual's choice to use a trail, however, is a function of his or her preferences, personal characteristics, neighborhood, trail accessibility, and trail characteristics. This research does not address each of these factors discretely, and it provides no direct evidence related to user preferences. Complementary research designs that incorporate surveys of users and nonusers are needed to develop more complete models of trail use.

The model accounts for important neighborhood characteristics, but some of the measures are crude, and it does not explore potential interactions among the socio-demographic and urban form variables. Refinement of measures such as percent commercial and analyses of interactions among variables may yield interesting results. In addition, the model accounts for characteristics of trail segments only indirectly and to the extent they affect neighborhood measures. The model does not include direct measures of trail characteristics that might influence use. For example, the model does not include variables related to trail surface, the availability of drinking water and restrooms, or the quality of contiguous landscapes. Similarly, the model incorporates a measure of the availability of parking in the neighborhood, but this measure could be refined or supplemented with measures of the availability of parking at access points or along streets contiguous to trails. These types of measures could be incorporated in future models but would require additional field work.

New technologies are becoming available that offer the potential for the development of measures such as the quality of the visual environment. For example, light detection and ranging (LIDAR) data, which are the optical equivalent of sonar and radar, provide information that analysts can use to distinguish vegetation from hard surfaces in the visual environment. These data can be analyzed to provide measures of viewsheds along trails that are analogous to measures of land use mix. In the future it may be possible, for example, to test whether trail traffic is correlated with the proportion of a viewshed along a trail segment that is vegetation.

These analyses are limited to monitoring results for a five-trail network in Indianapolis, Indiana. Indiana is in a temperate climate zone where seasonal effects are significant but not as great as in regions further north. Replication of this approach in other climatic regions where seasonal patterns differ would provide useful comparative information.

In addition to the refinement of the existing model through incorporation of new measures, it may be possible to explore other health-related behavioral issues through creative use of monitoring data. For example, air quality officials declare alerts and urge individuals to limit outdoor physical activity when models indicate that ozone levels will exceed standards.[38] By incorporating variables for days when alerts were declared, this modeling approach could be used to assess whether alerts reduced trail use. Other novel applications that provide useful insights likely will be identified as this approach to monitoring becomes more widespread.

Conclusions

These results reveal significant spatial and temporal variation in traffic on multiuse urban trails. Traffic varies across trails and on different segments of individual trails by time of day, day of week, and month of year. Trail traffic is significantly correlated with neighborhood characteristics. Approximately 80% of the variation in daily trail traffic can be explained by measures of urban form and socio-demographics in trail monitor neighborhoods, temporal control variables, and weather control variables. The regression model can be used to estimate traffic on trail segments in urban neighborhoods in Indianapolis, but additional research is needed to account for characteristics of trail segments, to integrate results with studies of individual behavior, to validate the model, and to extend the model for use in other regions.

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