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Can Money Buy Green? Demographic and Socioeconomic Predictors of Lawn-Care Expenditures and Lawn Greenness in Urban Residential Areas

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It is increasingly important to understand how household characteristics influence lawn characteristics, as lawns play an important ecological role in human-dominated landscapes. This article investigates household and neighborhood socioeconomic characteristics as predictors of residential lawn-care expenditures and lawn greenness. The study area is the Gwynns Falls watershed, which includes portions of Baltimore City and Baltimore County, MD. We examined indicators of population, social stratification (income, education and race), lifestyle behavior, and housing age as predictors of lawn-care expenditures and lawn greenness. We also tested the potential of PRIZM market cluster data as predictors for these two dependent variables. Lawn greenness was found to be significantly associated with lawn-care expenditures, but with a relatively weak positive correlation. We also found lifestyle behavior indicators to be the best predictors for both dependent variables. PRIZM data, especially the lifestyle segmentation, also proved to be useful predictors for both.

Keywords Baltimore, lifestyle behavior, long-term ecological research (LTER), NDVI, population, social stratification, urban ecology, urban lawn

This article examines demographic and socioeconomic predictors of residential lawn-care expenditures and lawn greenness at a household level in urban residential areas in Baltimore, MD. The motivations for this focus are practical, methodological,

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and theoretical. From a practical perspective, lawns are important for several reasons. The lawn is a typical American landscape feature and nearly omnipresent throughout the country (Jenkins 1994; Sternberg 2006). With the expansion of urban areas and residential development, turf grass has become a dominant land cover type in urban areas (Robbins and Birkenholtz 2003). It is estimated that there are 10 to 16 million hectares of lawn in the continental United States, an area larger than some major U.S. crops such as barley, cotton, and rice (Robbins and Birkenholtz 2003; Milesi et al. 2005).

Lawns may play an important ecological role in human-dominated landscapes. For example, lawns contribute to the mitigation of urban heat island effect (Spronken-Smith, Oke, and Lowry 2000), carbon sequestration (Bandaranayake et al. 2003), and enhanced infiltration and attenuation of stormwater runoff compared to bare soil or impervious surfaces (Brabec, Schulte, and Richards 2002). However, residential lawns may also significantly impair water quality through the use of lawn chemicals and overfertilization (Robbins and Birkenholtz 2003), diminish air quality because of lawn mower emissions (Priest, Williams, and Parton 2000), and greatly increase water consumption due to lawn irrigation (Robbins and Birkenholtz 2003; Milesi et al. 2005).

Cities have begun to establish Offices of Sustainability and to focus on the role urban areas play in global and regional ecologies, including heat island effects, carbon offsets through sequestration and avoidance, and water consumption and stormwater runoff (Maryland Department of Natural Resources 2007). Lawns may have an important ecological role in these dynamics. For instance, a number of studies have investigated the contributions of high-input, monocultural lawns to environmental quality, especially to water quality, with increasing concerns of urban lawns as non-point pollutant sources (Law, Band, and Grove 2004). However, very limited information is available on urban lawn-care practices, especially how household demographic and socioeconomic characteristics influence lawn care practices (Law et al. 2004; Osmond and Hardy 2004). Though a few studies have shown that the use of lawn-care inputs, especially chemicals, is positively associated with income and education (Robbins, Polderman, and Birkenholtz 2001; Osmond and Hardy 2004), housing value, and age of development (Law et al. 2004; Osmond and Hardy 2004), studies of how households manage their lawns and the factors affecting their management are still largely lacking (Robbins et al. 2001). In order to design and target local outreach and marketing campaigns to maximize the benefits and minimize the ecological costs of lawns, an examination of demographic and socioeconomic predictors of residential lawn-care expenditures and lawn greenness at a household level is crucial.

Research focused on demographic and socioeconomic predictors of residential vegetation in urban areas has focused on the extent and composition of vegetation structure and not on vegetation function, such as productivity, vigor, or health. Many of these studies have examined the relationship between population density or social stratification and the distributions or extent of vegetation in urban ecological systems. For instance, Iverson and Cook (2000) found that tree cover in Chicago was negatively correlated with population density. Researchers found that socioeconomic status was an important predictor of plant species composition (Whitney and Adams 1980), diversity (Hope et al. 2003), and richness (Martin, Warren, and Kinzig 2004). Socioeconomic status has also been found to be significantly associated with vegetation distribution on private lands and public rights-of-way (Grove et al. 2006b), and potential space for vegetation planting (Troy et al. 2007).

A number of studies have also examined the utility of additional demographic characteristics associated with lifestyle behaviors such as household composition, ownership type, and residence duration to predict the distribution of urban vegetation cover (Grove et al. 2006b), urban vegetation structure (Grove et al. 2006a), and potential for greening (Troy et al. 2007). The inclusion of these lifestyle characteristics provided better results for predicting vegetation cover and structure on private lands than using population density and socioeconomic status alone (Grove et al. 2006a, 2006b; Troy et al. 2007).

The linkage between these lifestyle characteristics and urban vegetation is associated with the social differentiation among urban neighborhoods that frequently becomes manifest in terms of lifestyle choices that households make and how those choices change over time (Bourdieu 1984). In the case of urban ecology, Grove et al. (2006b) have termed this phenomenon "an ecology of prestige," referring to the phenomenon in which household patterns of consumption and expenditure on environmentally relevant goods and services are motivated by group identity and perceptions of social status associated with different lifestyles. In this case, a household's land management decisions are influenced by its desire to uphold the prestige of its community and outwardly express its membership in a given lifestyle group (Grove et al. 2006b).

A critical dimension that may be missing from the focus on population density, socioeconomic status, and lifestyle characteristics is a temporal component. A number of studies have shown that age of housing is significantly associated with plant species composition (Whitney and Adams 1980), diversity (Hope et al. 2003), and abundance (Martin et al. 2004). Moreover, researchers have found that age of housing is an important predictor for lawn fertilizer application levels (Law et al. 2004), distribution of vegetation (Grove et al. 2006b), and patterns of vegetation and potentials for greening (Troy et al. 2007). Thus, the combination of lifestyle characteristics and housing age may improve the capacity to predict variations in lawn greenness on residential lands.

The ability to examine the relationships among demographic and socioeconomic predictors of lawn-care expenditure and lawn greenness at a household level in urban residential areas depends upon the availability of social and ecological data at a high resolution. Thus, certain methodological requirements exist. These requirements include spatially explicit databases that identify, select, and characterize individual parcels associated with each residential household in terms of both social and ecological phenomenon, including lawns and their greenness, population density, household socioeconomic status and lifestyle characteristics, and lawn-care practices. In some cases these data are available at a household level, and in other cases they are available at a U.S. Census Block Group level. Although comparable methods have been developed to examine variations in vegetation structure and extent (Grove et al. 2006a, 2006b; Troy et al. 2007), methods have not been developed to examine variations in ecological function, including vegetation greenness, for urban areas in combination with demographic and socioeconomic data that are at a parcel level yet spatially extensive for a region.

Research Questions

Based upon the focus and motivations we have discussed, we address two questions in this article: (1) What is the relative significance of population density, social stratification, lifestyle characteristics, and house age to variations in lawn-care expenditures and lawn greenness on residential private lands? (2) What is the relative significance of lawn-care expenditures to lawn greenness?

To address these questions, we use two sets of predictor variables of household and neighborhood characteristics, specifically, the PRIZM (Potential Rating Index for Zipcode Markets) categorization system and a number of continuous variables associated with population density, socioeconomic status, lifestyle characteristics, and house age (Troy et al. 2007). We measure lawn greenness by a vegetation index derived from remotely sensed data, the Normalized Difference Vegetation Index (NDVI). NDVI is a suitable vegetation index for measuring lawn greenness for several reasons. First, NDVI has been widely used to estimate vegetation growth, activity and productivity (Ricotta et al. 1999; Hill et al. 2004). Second, the ratioing of NDVI reduces many forms of multiplicative noise that present in multiple bands of multiple-date imagery (Jensen, 2000), allowing meaningful comparisons of seasonal and inter-annual changes in vegetation growth and activity. Third, NDVI can be easily obtained from remotely sensed imagery, which can be gathered for a large area in a cost-effective way. Hence, it can provide a useful index for studies carried out on large areas. We include lawn-care expenditures because it may be an important indicator of lawn care practices for two reasons. First, lawn-care expenditures on environmentally relevant goods and services are potentially motivated by conceptions of social identity, prestige, and status associated with green lawn idyll. Second, expenditures on lawn supplies can potentially be used to predict lawn fertilizer application rates, which are associated with lawn greenness (Zhou, Troy, and Grove 2008). However, because lawn health is dependent on many site-level environmental factors (e.g., soil type, drainage), as well as lawn-care practices, like frequency of irrigation, expenditures on lawn supplies are expected to be only a partial predictor of greenness. However, controlling for these environmental factors is beyond the scope of this current study.

Methods

Site Description

This research focused on the Gwynns Falls watershed, a study site of the Baltimore Ecosystem Study (BES), a long-term ecological research project (LTER) of the National Science Foundation (www.beslter.org). The Gwynns Falls watershed, with an area of approximately 171.5 km^2, lies in Baltimore City and Baltimore County, Maryland, and drains into the Chesapeake Bay (Figure 1). Land use in the Gwynns Falls watershed varies from highly developed in the lower sections to a broad mix of uses in the middle and upper sections. The percentage of residential land use in the Gwynns Falls watershed was about 38%, and residential lawn coverage was approximately 27.1% in 1999. The total population in the watershed was about 348,000 in 2000, with a population density of 2029 persons/km^2. Total population and population density varied among sub-watersheds, with the lower sub-watersheds of the Gwynns Falls being the most densely populated. The socioeconomic characteristics of residents vary greatly in the Gwynns Falls watershed. For instance, the average median household income in the upper sections was \$52,378, but only \$25,217 in the lower sub-watersheds in 2000.

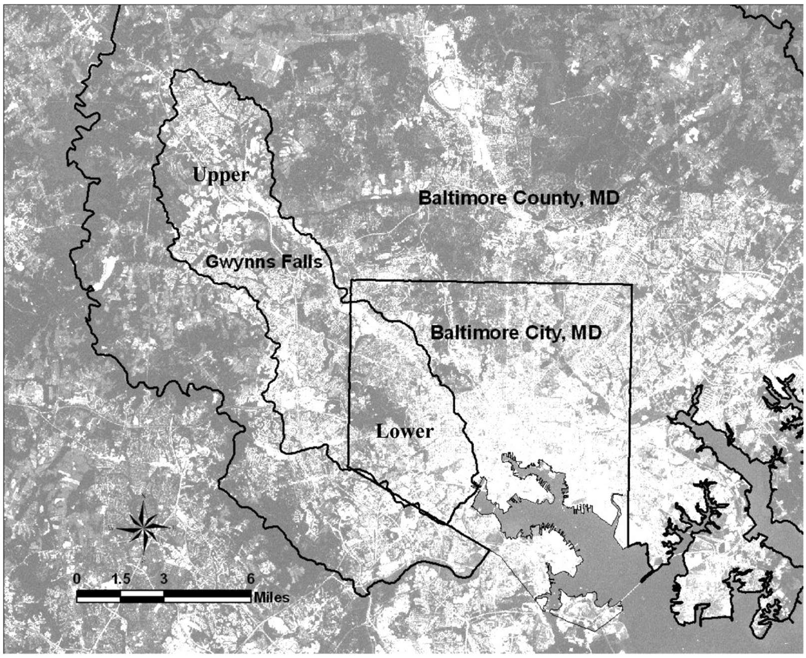

Figure 1. The Gwynns Falls watershed includes portions of Baltimore City and Baltimore County, Maryland, and drains into the Chesapeake Bay.

Data Collection and Preprocessing

Block Group Boundaries and Parcel Boundaries

A GIS data layer of Census Block Groups was created for the Gwynns Falls watershed by clipping the Geographic Data Technology (GDT) Dynamap Census data to the Gwynns Falls watershed boundary. We retained block groups being mainly ($\geq$50%) within the watershed, with areas larger than 50,000 m^2. This block group boundary layer served as the common boundary for all geospatial operations.

Property parcel boundaries were obtained in digital format from Baltimore County and Baltimore City. As we were only interested in private residential lawns, we selected out parcels with land use types of (1) residential dwelling, (2) residential commercial dwelling, (3) townhouse, and (4) residential condominium.

Socioeconomic and Lifestyle Behavior Data

The PRIZM system, which was developed for market research (Weiss 2000; Holbrook 2001), was used to measure population density, social stratification, and lifestyle behavior for several reasons. First, the three levels of aggregation, PRIZM 5, 15, and 62, correspond to population density, social stratification, and lifestyle behavior, respectively. The five classes of PRIZM 5 categorize neighborhoods by the degree of urbanization. The five clusters are disaggregated into 15 classes by incorporating socioeconomic status. The 62 PRIZM classes reflect the neighborhood lifestyle by combining urbanization and socioeconomic status with lifestyle components including household composition, mobility, ethnicity, and housing characteristics (Claritas

Table 1. Constituent variables of PRIZM segmentations; shaded boxes indicate that variables are included (adapted from Troy et al. 2007)

	PRIZM classification		
Variable	Urbanization (PRIZM 5)	Socioeconomic status (PRIZM 15)	Lifestyle (PRIZM 62)
Urbanization	■	■	■
Population density			
Housing			
Housing density	■	■	■
House value		■	■
Social rank			
Education		■	■
Occupation		■	■
Household income		■	■
Ethnicity			
Race/ancestry		■	■
Household composition			
Age of population			■
Family type			■
Mobility			
Owner/renter			■
Tenure duration			■

1999). Table 1 lists the types of continuous variables upon which social stratification and lifestyle dimension are built. Second, PRIZM is designed to predict variations in expenditures on different types of consumer goods and services, such as lawn-care supplies and services (Troy et al. 2007).

The PRIZM category for each block group was obtained from the Claritas 2003 database. Each block group was assigned a unique PRIZM category. In our data set, not all PRIZM classes are present; PRIZM 5, 15, and 62 have 4, 9, and 26 classes represented, respectively. We eliminated class 4 in PRIZM 5, since there was only one observation for this class. Therefore, PRIZM 5 only has three classes in our analysis.

We also used a set of continuous indicators of population, socioeconomic status, household characteristics, and ethnicity at the Census Block Group level, which were derived from the Geolytics Census 2000 attribute database (Geolytics 2000; Troy et al. 2007). Table 2 lists the description, minimum, maximum, mean, median, and standard deviation for each of the indicators. We included those variables to test which component variables of PRIZM segmentations are most significant to predict variations in lawn greenness and lawn-care expenditures.

Lawn-Care Expenditure and Lawn Greenness Data

Lawn-care expenditure data for each block group were obtained from the Claritas 2003 PRIZM database (http://www.claritas.com). Data for five indicator variables

Table 2. Description of lawn greenness, lawn-care expenditures, and continuous predictor variables

Variable	Description	Minimum	Maximum	Mean	Median	Std. dev.
Dependent variables						
Greenness	Lawn greenness measured by NDVI (unitless)	0.184	0.540	0.302	0.319	0.059
exp_total	Total lawncare expenditure ($000)	132.17	669.35	319.71	310.07	99.47
exp_service	Expenditure on lawncare services ($000)	16.67	339.49	138.83	132.38	45.45
exp_supply	Expenditure on lawncare supplies ($000)	69.73	243.71	138.85	135.48	36.32
exp_equip	Expenditure on equipment repair/rental ($000)	0.00	14.95	6.11	6.02	2.61
exp_machi	Expenditure on yard machinery ($000)	0.00	87.89	35.92	35.51	17.84
Predictor variables						
popD	Population density (per km^2)	149	13630	4608	3834	3052
income	Median household income ($)	9177	80656	34531	32223	14627
p_bach	Percent of people 25 years and over with at least a college degree (unitless)	0	0.381	0.095	0.069	0.083
h_value	Median home value ($)	13200	262500	74306	69700	33346
hh_size	Median household family size (person)	2	4	2.7	3	0.559
p_marriage	Percent of population (15 years and older) married (unitless)	0	0.971	0.496	0.479	0.195
p_withchild	Percent of households that have children under 18 years old (unitless)	0	0.567	0.199	0.191	0.128
p_h_owner	Percent of owner-occupied housing (unitless)	0	1	0.577	0.586	0.231
p_white	Percent of population that is "white" (unitless)	0	0.996	0.211	0.047	0.285
HA	Median house age (years)	3	115	63	65	24.23

were used, including total household lawn-care expenditure and its four subcomponents: expenditures on (1) lawn-care services, (2) lawn supplies, (3) repair/rental of lawn mowing equipment, and (4) yard machinery. Annual household values for the five variables of lawn-care expenditures were assigned to each block group.

Lawn greenness was measured by lawn NDVI. Specifically, we used the mean of lawn NDVI by block group as an indicator of lawn greenness, which was assigned to each block group. In this study, NDVI data were obtained from the Emerge color-infrared aerial imagery acquired in October 1999, with pixel size of about 0.6 m. The formula of NDVI is given by:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

where NIR is the reflectance in the near-infrared waveband, and RED is that of the red waveband. NDVI values range from -1 to 1, but typically between 0.1 and 0.7 for vegetation (Jensen 2000). Higher index values are associated with higher levels of healthy vegetation cover and higher possible density of vegetation.

The mean of lawn NDVI for each block group was obtained by first calculating the mean of lawn NDVI at the parcel level, which was then summarized by block group. We limited the calculation on the private residential lawns by using a thematic layer as a mask, which was derived from the land cover data for the Gwynns Falls watershed (Zhou and Troy 2008). The land cover data were derived from the same Emerge imagery as used for NDVI calculation. The overall accuracy of the classification was 92.3%, with the user's accuracy of 94.9% and the producer's accuracy of 89.3% for the class of herbaceous vegetation (Zhou and Troy 2008). As no lawn greenness information was available from those shaded lawn areas, we eliminated the effects of those possibly shaded lawns by excluding those pixels with brightness less than 40, when performing the summarization.

Statistical Analyses

We used multiple linear regressions to determine which combination of variables best predicts variance in each of six response variables, all averaged by block group: (1) lawn greenness; (2) total lawn-care expenditure; (3) expenditure on lawn-care services; (4) expenditure on lawn supplies; (5) expenditure on repair/rental of lawn mowing equipment; and (6) expenditure on yard machinery. Seven models were compared for each response variable, yielding 42 models (see Table 3 as an example). Those seven models have a given dependent variable as a function of: (1) median housing age; (2) population density; (3) population density +housing age; (4) socioeconomic status; (5) socioeconomic status +housing age; (6) lifestyle behavior characteristics; and (7) lifestyle behavior characteristics +housing age. We used median household income and the percent of people aged 25 years and over with at least a bachelor degree as measures of neighborhood socioeconomic status. In addition to population density and socioeconomic status, six continuous variables of household characteristics and ethnicity were used to measure lifestyle behaviors. Table 2 lists the descriptive statistics for each variable. The total number of observations was 302. House age is specified as a quadratic term ($HA + HA^2$) because previous research has shown that house age and vegetation likely have a nonlinear relationship (Grove et al.

Table 3. Summary results for linear regression models predicting lawn greenness

Model	Explanatory variables/parameter estimates	Adjusted AIC	Rank	Akaike weight (%)	R squared
LG1	HA, HA^2 0.0016***, −0.0000194***	−884.0	14	0.00	.1094
LG2	popD −8.47E–6***	−916.3	7	0.00	.1943
LG3	popD, HA, HA^2 −7.15E–6***, 0.00119**, −1.30E–5***	−924.6	4	0.00	.2266
LG4	Income, p_bach 6.97E–7**, 0.166***	−896.4	11	0.00	.1451
LG5	Income, p_bach, HA, HA^2 3.98E–7, 0.179***, 0.0017***, −1.62E–5***	−906.3	10	0.00	.1839
LG6	popD, income, p_bach, p_white, hh_size, h_value, p_marriage, p_withchild, p_h_owner −3.75E–6***, 3.01E–8**, −0.059, −0.010, 7.09E–4**, 7.46E–7***, 0.0434, 0.0025, −0.042**	−946.5	3	0.03	.3103
LG7	popD, income, p_bach, p_white, hh_size, h_value, p_marriage, p_withchild, p_h_owner, HA, HA^2 −3.16E–6**, 1.87E–7, −0.037, −0.0049, 6.09E–4**, 7.4E–7***, 0.025, 0.0051, −0.053***, 0.0016***, −1.34E–5***	−953.7	2	0.99	.3362
LG8	popD, hh_size, h_value, p_h_owner, HA, HA^2 −3.27E–6***, 0.000585**, 7.8E–7***, 0.0415***, 0.00165***, −1.0E–5***	−962.9	1	98.98	.3328
LGp1	PRIZM5	−916.7	6	0.00	.2085
LGp2	PRIZM15	−912.9	9	0.00	.2216
LGp3	PRIZM62	−891.5	13	0.00	.2671
LGp4	PRIZM5, HA (0.00141***), HA^2 (−1.2E–5***)	−920.8	5	0.00	.2322
LGp5	PRIZM15, HA (0.00139***), HA^2 (−1.17E–5***)	−915.9	8	0.00	.2422
LGp6	PRIZM62, HA (0.00131**), HA^2 (−1.12E–5**)	−893.4	12	0.00	.2832

*Significant at the 90% confidence level; **significant at the 95% confidence level; ***significant at the 99% confidence level.

2006b; Troy et al. 2007). A series of linear regressions was also performed to determine how lawn greenness was related to lawn-care expenditures.

Additional analyses were performed to examine the potential of the PRIZM categorizations on predicting lawn-care expenditures and lawn greenness. Thirty-six additional regressions were performed and compared to determine which combinations of PRIZM categorization (5, 15, or 62 categories) and median house age best predict variation in each of those six response variables (see Table 3 as an example).

We used multimodel inferential procedures (Burnham and Anderson 2002) to determine which of those variables or some combinations best explain the variation in each of the six response variables. This procedure is based on minimization of Akaike's information criterion (AIC) (Akaike 1973). Specifically, the "best" model is the one with the smallest AIC value among a set of candidate models. In this study, we used the adjusted AIC considering the relatively small ratio of the number of observations to the free parameters (Burnham and Anderson 2002). We also calculated the Akaike weight, the probability of a given model being the best one among a number of candidate models. Akaike weights are especially useful when the difference of AIC values between two models is small (Burnham and Anderson 2002). For each of the six response variables, multimodel comparisons are conducted to yield one "best" model amongst the 13 candidate models. In an attempt to simplify the "best" model, we examine the significance of the coefficients and run a regression on only those predictors with significant effects. We then compare this simplified model with the "best" model to obtain the final "best" model. We also performed multi-model comparisons separately among PRIZM models to examine the relative significance of PRIZM 5, 15, or 62 on predicting lawn-care expenditure and lawn greenness.

Results

Significance of Population Density, Social Stratification, Lifestyle Characteristics, and House Age as Predictors of Lawn-Care Expenditures and Lawn Greenness

We summarize our results in terms of continuous variable models, categorical variable models, and comparisons of continuous and categorical variable models. For our continuous variable models, about 75% of variance in total lawn-care expenditure was explained jointly by income, percent college graduates, median house value, and percent of owner-occupied house ($R^2 = .754$). The coefficients of the four predictors are all positive and significant at the 99% confidence level (Table 4). Variation in each of the four subcomponents of total expenditure is best explained by lifestyle behavior indicators. These models are very effective in predicting the lawn-care expenditure components. For instance, 84% of variation in expenditures on yard machinery was explained in model YM. Percent college graduates, median house value, and percent of owner-occupied house are significant predictors for all of the four models (see Table 4). Other significant predictors include median household income (LU, YM), percent of households with children under age 18 years (LR), family size (YM), and house age (LU, LR).

For our categorical models with total lawn-care expenditure and each of its four subcomponents, the model using PRIZM 62 and house age as predictors is the best (Table 5). When comparing PRIZM models with those using continuous variables as predictors in the same model group, the best continuous variable model is superior

Table 4. Summary results of the best models for total lawn-care expenditures and its four broken down components, using continuous variables

Model	Response variable	Explanatory variables/parameter estimates							R squared
LET	Total lawn-care expenditure	Income 0.00104***	p_bach 198.74***	h_value 0.000437***	p_h_owner 263.82***				0.7542
LS	Expenditure on lawn-care services	p_bach 119.22***,	h_value 0.000195***	P_h_owner 135.39***					0.7386
LU	Expenditure on lawn-care supplies	Income 0.000533***	p_bach 57.57***	h_value 0.000178***	p_h_owner 78.38***	HA 0.436***	HA^2 −0.00425***		0.7609
LR	Expenditure on equipment repair/rental	p_bach 4.99***,	h_value 1.5E–5***	p_marriage 1.33**	p_withchild −1.91**	p_h_owner 7.89***	HA 0.024**	HA^2 −2E–4**	0.809
YM	Expenditure on yard machinery	Income 0.000151**	p_bach 33.79***	hh_size 0.343***	h_value 0.000103***	p_h_owner 50.00***			0.8414

*Significant at the 90% confidence level; **significant at the 95% confidence level; ***significant at the 99% confidence level.

Table 5. Summary results of the best models for total lawn-care expenditures and its four broken down components, using PRIZM categories

Model	Response variable	Explanatory variables/ parameter estimates	R squared
LETP	Total lawn-care expenditure	PRIZM62, HA (1.457**), HA^2 (−0.0158***)	.6697
LSP	Expenditure on lawn-care services	PRIZM62, HA (0.4664*), HA^2 (−0.00514**)	.6326
LUP	Expenditure on lawn-care supplies	PRIZM62, HA (0.6498***), HA^2 (−0.00694***)	.674
LRP	Expenditure on equipment repair/rental	PRIZM62, HA (0.0502***), HA^2 (−0.00054***)	.621
YMP	Expenditure on yard machinery	PRIZM62, HA (0.291***), HA^2 (−0.00319***)	.6587

*Significant at the 90% confidence level; **significant at the 95% confidence level; ***significant at the 99% confidence level.

to the best PRIZM model, suggesting the more explanatory power of continuous variables than categories using the PRIZM system.

For the continuous variable models for lawn greenness, the best is LG8 (Table 3), in which 33% of variation in lawn greenness was explained jointly by population density, mean family size, median house value, percent of owner-occupied housing, and house age, with the most variation explained by median house value. In the model group using PRIZM categorizations as predictors, LGp4 (PRIZM5 + house age) is the best model. However, this does not necessarily mean that population density is a better predictor of lawn greenness than socioeconomic status or lifestyle behavior, as the continuous variable model LG8 containing lifestyle factors and house age was clearly superior to the categorical model LGp4 (Table 3). Rather, it might suggest that the loss of parsimony introduced by the inclusion of social stratification or lifestyle behavior categories outweighs their contributions to explanatory power for the comparisons among categorical models.

The significance tests on the coefficients show that all house age coefficients are significant for all lawn greenness models where they appear, most at the 99% significance level (Table 3). Including house age in its quadratic form significantly improved these models. Both the untransformed term and the squared term are significant at the 95% confidence level for most but not all of the lawn-care expenditures models. In all cases the effect of house age is significant, the coefficient on the untransformed variable is positive, ranging between 0.00157 and 2.498, and the squared term is negative, ranging between −0.0366 and −1.0E–5. This suggests a parabolic relationship between house age and lawn greenness, and lawn-care expenditures.

Table 6. Correlation coefficients between lawn greenness and lawn-care expenditures

	exp_total	exp_service	exp_supply	exp_equip	exp_machi
Greenness	0.24 ($p < .01$)	0.17 ($p < .01$)	0.30 ($p < .01$)	0.22 ($p < .01$)	0.26 ($p < .01$)

Significance of Lawn-Care Expenditures to Lawn Greenness

Lawn productivity is significantly associated with total lawn-care expenditure and its four subcomponents. However, only relatively weak positive correlations are found (Table 6).

Discussion

Theoretical Implications

In all cases, lifestyle variables, which include levels of urbanization and socioeconomic status, were the best predictors of lawn-care expenditures and lawn greenness. This suggests that household land management decisions such as lawn-care expenditures, and in turn lawn greenness, are influenced by a household's life stage and desire to assert its membership in a given lifestyle group in a neighborhood context.

Among the lifestyle factors, we found that the percent of owner-occupied house (*p_h_owner*) was the most significant one in predicting lawn-care expenditures. The positive relationship implies that higher lawn-care expenditures would be associated with owner-occupied houses. For lawn greenness, surprisingly, the coefficient of the percent of owner-occupied house was significantly negative, which could suggest a negative effect of owner-occupied housing on lawn greenness. However, our field observations suggest that it might also be the case that owners of large parcel lots maintain a primary and secondary lawn (Zhou et al. 2008)—mown and unmown—and that the greenness values for these two types of lawns are different. In this case, the combination of the greenness values for these two types of lawns and its effects on the model need to be further explored.

Median house value (*h_value*) is another significant predictor in all the "best" models. The positive coefficients on median house value indicate that higher lawn-care expenditures and greener lawns would be expected in homes with higher market values. Other lifestyle indicator variables, such as family size (model LG8, YM), percent of population married, and percent of household with children (model LR), are important predictors of lawn-care expenditure and lawn greenness.

Population density alone is inadequate for predicting lawn-care expenditure and lawn greenness. Population density is not significantly associated with lawn-care expenditure, when adjusting effects of lifestyle behavior. However, population density is a significant predictor of lawn greenness (Table 3). Results show that socioeconomic status (income, education) is an important predictor of lawn-care expenditure and lawn greenness on private residential lands. For each of the six response variables, models using socioeconomic status alone yielded significant results. When lifestyle factors were added to the models, education attainment and income were significant in explaining most of the lawn-care expenditure indicators (Table 4). In all cases where the effects of income and education were significant, the coefficients were positive, suggesting that higher lawn-care expenditures and lawn greenness would be associated with higher socioeconomic status.

However, socioeconomic status is not sufficient for predicting lawn-care expenditure and lawn greenness. Our analyses indicate that including additional household characteristics associated with lifestyle behavior provides better results for all cases. These findings are consistent with the previous studies on vegetation distribution and space available for vegetation planting (Grove et al. 2006b; Troy et al. 2007).

The results show that PRIZM categorization systems are useful predictors of lawn-care expenditures and lawn greenness. When comparing the six PRIZM models for total lawn-care expenditure and its four components, the most complex model, PRIZM 62 (lifestyle cluster) and house age, is the best. This suggests lifestyle behavior is a better predictor of lawn-care expenditure than socioeconomic status (PRIZM 15) and population density (PRIZM 5). The results are consistent with the analyses where continuous social variables were used.

House age proved to be an important predictor of lawn-care expenditure and lawn greenness, as both the linear term and the squared term were significant in most of the models that include those terms. This parabolic relationship between house age and lawn-care expenditure, as well as lawn greenness, has also been found between house age and vegetation distribution (Grove et al. 2006b), and space for planting (Troy et al. 2007). One possible reason for less expenditure on older neighborhoods might be that older housing stock tends to have smaller lot size and larger lot coverage, and thus less room for lawn (Troy et al. 2007).

Lawn greenness is significantly correlated with total lawn-care expenditure, as well as its four subcomponents. However, those relationships were relatively weak. This is consistent with our expectation that lawn-care expenditures are only a partial predictor of lawn greenness and that many other factors are of significant importance. In particular, it is expected that lawn-care routines, such as the frequency and method of irrigation (which may be uncorrelated with lawn-care expenditures), as well as biophysical factors, such as soil type, aspect, climatic conditions, and predominant turf species, significantly influence lawn greenness. The capacity of lawn-care expenditures in combination with these types of factors to predict lawn greenness should be further explored. It is also worth noting that the data for the models were not obtained at the same year. Particularly, the NDVI data that were used to measure lawn greenness were acquired in 1999, whereas the lawn-care expenditure data were obtained from the 2003 database. Although little change in household lawn-care expenditures might be expected in a 4-year time period (i.e., from 1999 to 2003), relatively large year-to-year variation in NDVI might occur. In addition, NDVI data used in this study only provided one snapshot of lawn greenness in 1999. Therefore, this discrepancy in timing between the two databases (i.e., lawn greenness and lawn-care expenditure) used in this study might have diminished the correlation between lawn greenness and lawn-care expenditures, and may affect the model accuracy for lawn greenness.

Management Implications

The results from this research have significant implications for urban natural resource managers. Urban lawns provide a variety of important ecological benefits such as the mitigation of urban heat island effects (Spronken-Smith et al. 2000) and carbon sequestration (Bandaranayake et al. 2003). Urban lawns may also incur ecological costs such as nitrogen and phosphorous runoff, loss of biodiversity, loss of wildlife habitat, and consumption of water. Our research results demonstrate that household lifestyle behavior is an important predictor of lawn-care expenditures and lawn greenness. This connection between lifestyle, lawn-care practices, and lawn greenness suggests that a comprehensive environmental education program that targets different types and intensities of lawn-care practices associated with varying household lifestyles may be more effective than traditional, one-type-fits-all outreach campaigns (Grove et al. 2006b). For instance, the content of an environmental marketing campaign's message to maximize ecological benefits and minimize ecological costs of lawns may have to vary according to differences among neighborhoods' sense of prestige, identity, and status. The pathways for communicating may vary as well, depending upon the most effective forms of mass media by which to reach different lifestyle groups. Marketing firms do this already for various commercial products and brands including the lawn-care-chemical industry, which markets its products by using consumer profiles of lifestyle groups (Troy et al. 2007). These types of approaches are critical as programs such as the Chesapeake Bay Program attempt to reduce nutrient inputs in the Chesapeake Bay and local municipalities work to comply with total maximum daily loads (TMDLs) requirements associated with the Clean Water Act.

Our findings suggest novel opportunities for urban watershed modelers. Total lawn-care expenditure, as well as its four components, can be effectively predicted by social variables that are widely available and readily used from the U.S. Census. Using these Census data in a spatial context, it may be possible to build an urban hydro-ecological-social model with estimates of lawn fertilizer application rates based upon the relationships between application and expenditures, and between expenditures and household lifestyle characteristics derived from Census data. These spatial estimates of fertilizer application rates at the household or block group level may significantly enhance non-point-source modeling of urbanized and urbanizing watersheds.

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