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Influence of school environments on childhood obesity in California

Alberto M. Ortega Hinojosa[a,b], Kara E. MacLeod[c], John Balmes[a], Michael Jerrett[a,c,*]

[a] School of Public Health, University of California, Berkeley, Berkeley, CA 94720, United States
[b] IMPAQ International, LLC, Oakland, CA 94612, United States
[c] Fielding School of Public Health, University of California, Los Angeles, Los Angeles, CA 90095, United States

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ABSTRACT

Objective: To conduct a state-wide examination of public schools and the school neighborhood as potential targets for environmental public health tracking to address childhood obesity.

Methods: We examined the relationship of social and physical environmental attributes of the school environment (within school and neighborhood) and childhood obesity in California with machine learning (Random Forest) and multilevel methods. We used data compiled from the California Department of Education, the U.S. Geological Survey, ESRI's Business Analyst, the U.S. Census, and other public sources for ecologic level variables for various years and assessed their relative importance to obesity as determined from the statewide Physical Fitness Test 2003 through 2007 for grades 5, 7, and 9 (n = 5,265,265).

Results: In addition to individual-level race and gender, the following within and school neighborhood variables ranked as the most important model contributors based on the Random Forest analysis and were included in multilevel regressions clustered on the county. Violent crime, English learners, socioeconomic disadvantage, fewer physical education (PE) and fully credentialed teachers, and diversity index were positively associated with obesity while academic performance index, PE participation, mean educational attainment and per capita income were negatively associated with obesity. The most highly ranked built or physical environment variables were distance to the nearest highway and greenness, which were 10th and 11th most important, respectively.

Conclusions: Many states in the U.S. do not have school-based surveillance programs that collect body mass index data. System-level determinants of obesity can be important for tracking and intervention. The results of these analyses suggest that the school social environment factors may be especially important. Disadvantaged and low academic performing schools have a higher risk for obesity. Supporting such schools in a targeted way may be an efficient way to intervene and could impact both health and academic outcomes. Some of the more important variables, such as having credentialed teachers and participating in PE, are modifiable risk factors.

1. Introduction

In the U.S. more than a third of children and adolescents are overweight or obese (Ogden et al., 2014). Childhood overweight and obesity are major risks for serious youth outcomes and the effects can persist beyond childhood. Health outcomes include asthma, cancer, cardiovascular disease, type II diabetes, hypertension, and depression (Dietz, 1998). It is projected that poor diet and inactivity will soon overtake tobacco as the leading risk factor for cancer and the leading cause of preventable death in the U.S. (Mokdad et al., 2004; Eheman et al., 2012; Nichols et al., 2012).

Among children and adolescents, obesity has more than doubled since the 1970s (Hedley et al., 2004; Ogden et al., 2008). The mean body mass index of U.S. children and adolescents is increasing at a rate that is much too fast to be explained by a genetic change in the population and, therefore, is likely to be related to environmental factors (Hill and Peters, 1998). There is increasing evidence that social and physical environment influence obesity (Booth et al., 2005; Davison and Lawson, 2006; Frank et al., 2007; Dunton et al., 2009; Morland and Evenson, 2009).

Two reviews indicate that natural environment (e.g. green space) may support physical activity levels among children but the evidence is sparse or conflicting (Davison and Lawson, 2006; Dunton et al., 2009). Other physical environment components that have been identified as potential modifiable determinants of physical activity or obesity for children and adolescents include traffic and air pollution (Gauderman et al., 2007; Jerrett et al., 2010, 2013), personal safety (Committee on Environmental Health), and pedestrian facilities and traffic safety

* Correspondence to: Department of Environmental Health Sciences, Center for Occupational and Environmental Health, Fielding School of Public Health, University of California, Los Angeles, 650 Charles E. Young Drive S, Rm. 56-070 CHS, Mail Code: 177220, Los Angeles, CA 90095, United States
E-mail address: mjerrett@ucla.edu (M. Jerrett).

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(Davison and Lawson, 2006; Timperio et al., 2005). The food environment may also affect diet. Research on the food environment around the home (Galvez et al., 2009; Powell et al., 2007) and school (Jerrett et al., 2009) supports this notion. The within school environment can also support childhood nutrition (Story et al., 2009; Wang et al., 2010).

Public schools are good places to address weight-related behaviors because it is a global way to reach the youth population and children spend a substantial proportion of their time at school (Kriemler et al., 2011). Some school interventions have demonstrated increased physical activity, improved diet, and a decline in obesity (Veugelers and Fitzgerald, 2005; Zenzen and Kridli, 2009). The length of follow-up for these studies is insufficient to determine the long-term effects of the interventions (Zenzen and Kridli, 2009) and the impacts beyond the school environment are not always assessed (Kriemler et al., 2011). Nevertheless, the extant data support the notion that school interventions can be effective (Zenzen and Kridli, 2009; Foster et al., 2008; Evenson et al., 2009; Sharma, 2007; Summerbell et al., 2005; Probart et al., 2007). These interventions are especially effective when both education and environmental changes are included (Kriemler et al., 2011).

Existing efforts to address obesity have included the food and physical activity environment and school-based interventions for youth. Surveillance systems can be used to identify at-risk populations and to evaluate these obesity prevention efforts, including social factors; however, most systems in the U.S. collect a limited number of measures and most do not include environmental factors (Hoelscher et al., 2017). While behavioral surveys are also important for surveillance, sometimes self-reported weight and height can result in an underestimation of obesity prevalence (Hoelscher et al., 2017). School surveillance systems present an opportunity to monitor obesity as weight and height measurements can be incorporated into other routine screenings and because it is a global way to reach the youth population (Hoelscher et al., 2017). It can also be important to track characteristics at the system level that are known to determine obesity and that can be modified to reduce the risk of obesity. The objective of this paper is to examine the relationship between childhood obesity using 2003 through 2007 data from the California Physical Fitness Test (administered yearly to 5th, 7th and 9th graders) and numerous social and environmental characteristics of the within school space, the school neighborhood, and school county. This is the first state-wide study to look at public schools as potential targets for environmental public health tracking to identify at-risk populations to address childhood obesity.

2. Material and methods

2.1. Study population

By law, the State of California requires the yearly physical fitness testing of all 5th, 7th, and 9th graders in the state's public schools and maintains a database of the results through the California Department of Education. This yearly test is called the Physical Fitness Test (PFT) and is standardized through an official battery of tests called the FITNESSGRAM®. The data are considered repeated cross-sections as data from the same student are not identifiable over time due to student ID suppression in the data. Due to population size, two smaller counties did not provide data (Alpine and Trinity). Overall a majority of eligible students participate (e.g. 75% and 79% in 2003 and 2007 respectively). Participants of the PFT 2003 through 2007 constitute the study population for this paper. Data were excluded if relevant information were missing (n = 653,500); schools had fewer than 10 students (n = 2584); and weight values outside the biologically plausible range or if body mass index (BMI) was an outlier as determined from z-scores (n = 114,302). The final analytical dataset included schools with no missing data; thus, the analytic data set includes 5,265,265 student-level observations in more than 6,000 schools. All analyses of students were conducted on de-identified publicly available data. The study procedures were carried out in accordance with the Declaration of Helsinki.

2.2. Measures

Height and weight measurements from the FITNESSGRAM® were used to compute obesity rates for California public schools. Schools were allowed to choose between three methods: caliper test, bioelectric impedance, and BMI (kg/m2). BMI was the most common method (85%). BMI was recalculated from the height and weight data. Data were cleaned to exclude missing and outlier data. Childhood obesity was defined for children and adolescents based on the 2000 U.S. Centers for Disease Control and Prevention (CDC) Growth Charts comparing the BMI-for-age percentile ranking. The ranking compares the child's BMI to the distribution of BMI scores of other children of the same age and gender. Obesity is defined as being at or above the 95th percentile (CDC, 2017).

The independent variables assumed to influence these caloric consumption or energy expenditure can be divided into four hierarchies: Levels 1 (individual), 2 (school), 3 (school neighborhood or census tract), and 4 (school county) variables. The school and neighborhood change may be analyzed longitudinally using the PFT measures aggregated yearly at these ecologic scales. Additionally, other school-level attributes that are measured yearly and where available, year specific data were used. ZIP code level variables were considered but they all dropped out as part of the hierarchical screening process described below.

The only time-dependent variables available for analyses exist at the school (level 2) and neighborhood level (level 3; e.g. SES and other characteristics that can be determined from the Census), as it was not possible to obtain individual longitudinal data from the California Department of Education. The school and neighborhood change may be analyzed longitudinally using the PFT measures aggregated yearly at these ecologic scales. These are available since 2003. Additionally, there are other school-level attributes that are measured yearly and are applicable to the study such as the Academic Performance Index (API) score. Where available, year specific data were used.

2.3. Statistical analysis

Approximately 300 variables were considered. Variables were excluded in a hierarchical process. Step 1 involved assessing multicollinearity by identifying all covariates with absolute value of correlation greater than or equal to 0.8. We then compared standardized coefficients representing the association with the outcome (obesity) using univariate regression and removed the highly correlated variables that had the smaller association with the outcome. A handful of variables of potential policy interest were kept for further analysis even if they were correlated (e.g. the Academic Performance Index base score and percent of students in the Free or Reduced Meals Program), yielding a dataset with 124 variables. Step 2 involved making a decision about the remaining correlated variable pairs (|correlation| > 0.7-< 0.8). In this step, the relative importance was determined by ensemble machine learning Random Forest regression, yielding new datasets of 64, 67 and 69 variables for 5th, 7th and 9th grades, respectively. Step 3 involved a final screening of variables by eliminating variables that were captured as components of general variables (for example, murder, rape, and robbery were types of violent crime) and were not eliminated during the correlated variable screening process. Additionally, the county and ZIP code level variables were deemed relatively unimportant based on their relative low Random Forest ranking, which was supported by the evaluation of the variance explained by county-level variables. The final data sets consisted of 48 variables for 5th and 7th grade and 49 variables for 9th grade.

Table 1
Descriptive summary of key variables.

Level	Category	Source	Variable	Min	Max	Mean	Median	StDev	IQR	5%ile	95%ile
City	Crime	FBI	Property Crime (per 10 K)	0	52,553	333	303	432	128	155	575
City	Crime	FBI	Total Crime (per 10 K)	0	118,510	778	718	946	307	344	1359
City	Crime	FBI	Violent Crime (per 10 K)	0	6383	54	50	48	40	13	115
Outcome	Statistic	CDE - PFT	BMI Percentile	0.0%	99.9%	67.3%	75.1%	28.4%	45.9%	11.4%	98.7%
Outcome	Statistic	CDE - PFT	Obese (Dichotomous)	–	–	19.7%	–	–	–	–	–
Outcome	Statistic	CDE - PFT	Overweight or Obese (Dichotomous)	–	–	38.1%	–	–	–	–	–
Outcome	Statistic	CDE - PFT	County Mean BMI	20.1	23.0	21.8	22.0	0.5	0.8	21.2	22.3
Outcome	Statistic	CDE - PFT	County Percent Obese	8.7%	27.4%	19.6%	19.9%	3.2%	5.9%	15.4%	23.1%
Outcome	Statistic	CDE - PFT	School Percent Obese	0.0%	75.0%	19.7%	19.8%	7.8%	11.5%	6.7%	32.5%
School	Air Quality	Jerrett et al.	Nitrogen Dioxide (ppm)	2.8	15.8	10.1	10.1	1.8	2.4	7.4	12.8
School	Air Quality	Jerrett et al.	Particulate Matter 10 (ug/m^3)	15.6	34.2	29.5	31.1	4.5	6.7	20.4	34.0
School	Air Quality	Jerrett et al.	Particulate Matter 2.5 (ug/m^3)	4.5	23.8	14.6	15.4	3.3	5.1	8.8	18.8
School	Air Quality	Jerrett et al.	Particulate Matter 2.5 RS (ug/m^3)	2.0	17.9	11.0	11.4	3.5	6.1	5.5	16.2
School	API	CDE - API	Academic Performance Index	0.0%	100.0%	42.7%	40.2%	33.8%	63.9%	0.3%	97.8%
School	Food	NHC	Nearest Any Type(Km)	0.0	44.6	0.8	0.6	1.0	0.6	0.1	2.1
School	Food	NHC	Nearest Fast Food (Km)	0.0	112.6	1.6	1.0	3.0	1.0	0.3	3.9
School	Food	NHC	Nearest Supermarket (Km)	0.0	89.3	1.7	1.3	2.4	1.0	0.4	4.2
School	Food	NHC	All (1 km Network; Count)	0.0	146.0	4.6	3.0	6.0	6.0	0.0	16.0
School	Food	NHC	Fast Food (1 km Network; Count)	0.0	16.0	1.3	0.0	1.8	2.0	0.0	5.0
School	Land Use	ESRI BA	Avg Link Length (m) − 1 km Buffer	36	1388.5	106	99	50	25	71	153
School	Land Use	ESRI BA	Connectivity Index 1 km	0.02	0.69	0.33	0.33	0.13	0.19	0.12	0.54
School	Land Use	USGS	NDVI restandardized (1 km Euclidean)	0.18	0.74	0.45	0.45	0.04	0.05	0.38	0.52
School	Land Use	ESRI BA	Nearest Highway Distance (km)	0.00	49.41	1.85	1.20	2.43	1.52	0.20	5.38
School	Land Use	ESRI BA	Nearest Rec Facility Distance (km)	0.01	30.68	0.83	0.62	1.12	0.59	0.14	1.90
School	Land Use	NLCD	NLCD - Green Space 1 km	0.0%	100.0%	7.4%	1.1%	14.7%	6.7%	0.0%	40.4%
School	Land Use	NLCD	NLCD - Mean Development 1 km	0.00	2.95	1.40	1.44	0.59	0.84	0.32	2.28
School	Land Use	NLCD	NLCD - Park 1 km	0.0%	79.3%	11.4%	8.9%	9.7%	12.3%	0.8%	30.4%
School	Participation	CDE - PFT/ CBEDS	PE Teachers per 1000 Students (Best Combined)	0.0	25.7	2.4	2.7	1.8	3.7	0.0	5.1
School	Performance	CDE - API	Academic Performance Index	267	1000	716	710	95	133	565	882
School	Population	CDE - PFT	PFT Count by School by Year	10	1582	349	314	257	395	53	804
School	SES	CDE - API	English Learners	0.0%	100.0%	30.3%	24.4%	23.3%	35.4%	2.0%	75.9%
School	SES	CDE - API	Free or Reduced Meal Program	0.0%	100.0%	48.5%	48.0%	29.8%	52.0%	4.0%	99.0%
School	SES	CDE - API	FTE Teachers w/ Full Credentials per 50 Students	0.0	125.0	5.0	4.3	3.7	4.4	1.3	11.2
School	Transport	SWITRS	Pedestrian and Cyclist Vehicular Collisions Standardized by Road Length (1 km Network Buffer)	0.0	3.4	0.2	0.2	0.3	0.3	0.0	0.8
School	Transport	DynaMap	Traffic Density (1 km Network Buffer)	1564	195,055	45,560	43,708	20,236	27,297	16,081	81,227
Tract	SES	ESRI BA	Diversity Index (2006)	14.9	96.7	73.9	79.2	16.9	24.8	40.0	92.6
Tract	SES	ESRI BA	Housing Units - Owner Occupied (2006)	0.0%	98.3%	59.7%	62.1%	21.4%	32.9%	21.0%	89.3%
Tract	SES	ESRI BA	Housing Units - Vacant (2006)	0.3%	67.3%	5.0%	3.8%	4.9%	3.5%	1.3%	11.8%
Tract	SES	ESRI BA	Median Household Income (2006)	0	278,358	66,630	60,816	32,142	36,932	28,218	126,173
Tract	SES	ESRI BA	Unemployment (2006)	0.1%	100.0%	9.3%	8.1%	5.4%	6.6%	3.1%	19.6%
Tract	Transport	DynaMap	Average Time to Work (minutes)	0.0	59.7	28.2	27.9	6.0	6.9	19.3	38.6
Tract	SES	ESRI BA	Education - Mean Attained	0.00	4.00	2.58	2.59	0.68	0.99	1.61	3.65

API: Academic Performance Index.
CBEDS: California Basic Educational Data System.
CDE: California Department of Education.
ESRI BA: Environmental Systems Research Institute, Business Analyst.
FBI: Federal Bureau of Investigation.
NHC: California Department of Public Health, Network for a Healthy California.
NLCD: National Land Use Consortium Database.
PFT: Physical Fitness Test.
SWITRS: State-Wide Integrated Traffic Records System.
USGS: U.S. Geologic Survey.

We then assessed the relative importance of the school attributes using Random Forest, which consists of several correlated decision trees to classify the data. This method enables examination of the predictive contribution of each variable and ranks the importance of the covariates provided (Breiman, 2001; Shih, 2011).

Due to the inefficient recursive nature of the Random Forest algorithm, and the relatively large size of the dataset, we were forced to limit the analysis to a randomly selected 10% subset of the data (approximately yearly 160,000 data points or 800,000 in total) per each individual grade. A sensitivity analysis repeating the Random Forest process 10 times using random subsamples of the data with 10,000 data points revealed little change in each iteration. In the sensitivity analysis, the ranking order of any given variable changed by only one or two places and the importance point of inflection remained fixed, with the same set of top variables. Given that using less than 0.8% of the data points maintained stability in the relative importance of the variables, we assume that the results of the much larger random subset used for the purpose of this analysis are representative of the full dataset. For our final models, we used all variables with importance values higher than the importance inflection point as determined visually from plots.

In the next step, we fit the selected variables with a multilevel random effects model to account for the hierarchical structure of the data (i.e. students nested in schools). All modeling was conducted using *GAMEPHIT (*Krewski and Hughes, 2017*)*, a package that can analyze multilevel spatially correlated outcomes. The theoretical framework and operational details for *GAMEPHIT* have been published elsewhere (Krewski and Hughes, 2017; Ma, 1999; Ma et al., 2003). Individual-level (student-level) age, sex, and race and PFT year were included in all models. We explored spatial correlation using combinations of two-level and one-level distance decay and independent models clustered on county and school. The distance decay model assumed a basic adjacency matrix to define neighboring counties and schools. Schools were considered neighbors if they were within 5 km of each other. The multilevel model assumes the following form. For student i in school j, assuming u ~ multivariate normal (0,Σ); $\pi_{ij} = P(\text{obesity}_{ij} = 1)$:

$$logit(\pi_{ij}) = \beta_0 + \beta_1 age_{ij} + \beta_2 female_{ij} + \beta_3 race_{ij} + \beta_n year_{ij} + U_j + \varepsilon_{ij}$$

Variables were rescaled for interpretability. Percentage variables were recoded from 0 to 10 (0 = 0% and 10 = 100%) so that a unit change was equal to 10%. Count variables were rescaled by their respective 10–90th percentile range. Ordinal variable educational attainment was coded 1–4 where 1 can be interpreted as no high school diploma and 4 as having a graduate degree and then summarized at the school level. Indices and scores were not rescaled as they were interpretable in their original units. Monetary variables were rescaled to $10,000 increments.

We conducted a sensitivity analysis to compare the performance of the various models with the mean squared error (MSE) and the random effects variance. We compared: (1) a null model or unconditional model; (2) a basic model with only individual level variables (race, age, gender and PFT year); (3) the final model with the highest importance Random Forest variables; and (4) a long model including a large

Table 2
Variable rankings by grade.

	5th Grade (10%)			7th Grade (10%)			9th Grade (10%)		
Rank	Lev	Variable	Imp	Lev	Variable	Imp	Lev	Variable	Imp
1	**SCH**	**Academic Performance Index**	**1297**	**IND**	**Age**	**1043**	**IND**	**Age**	**868**
2	**SCH**	**% English Learners**	**1276**	**SCH**	**Academic Performance Index**	**754**	**SCH**	**Academic Performance Index**	**544**
3	**SCH**	**SE Disadvantaged**	**1183**	**SCH**	**% English Learners**	**628**	**SCH**	**% English Learners**	**463**
4	**SCH**	**Full Cred Teachers Per Student**	**1129**	**SCH**	**SE Disadvantaged**	**625**	**SCH**	**PE Teachers Per Student**	**454**
5	**IND**	**Age**	**1114**	**SCH**	**PE Participation**	**572**	**SCH**	**PE Participation**	**447**
6	**PL**	**Violent Crime**	**1012**	**SCH**	**PE Teachers Per Student**	**560**	**SCH**	**Full Cred Teachers Per Student**	**420**
7	**SCH**	**PFT Year**	**620**	**SCH**	**Full Cred Teachers Per Student**	**538**	**PL**	**Violent Crime**	**414**
8	**IND**	**Hispanic**	**548**	**PL**	**Violent Crime**	**519**	**IND**	**Hispanic**	**290**
9	**TR**	**Diversity Index**	**391**	**IND**	**Hispanic**	**467**	**SCH**	**PFT Year**	**267**
10	**IND**	**Female**	**340**	**IND**	**Female**	**353**	**IND**	**Female**	**234**
11	SCH	Distance to Nearest Highway	293	**IND**	**PFT Year**	**294**	**IND**	**Other Race**	**151**
12	SCH	Mean NDVI	292	**TR**	**Diversity Index**	**195**	**IND**	**Black**	**139**
13	SCH	Sinuosity (road)	291	**TR**	**Per Capita Income**	**175**	**TR**	**Mean Education Attained**	**136**
14	SCH	Food: Dist Produce Market	286	SCH	Mean NDVI	154	**IND**	**Asian**	**128**
15	SCH	Traffic Density	285	SCH	Distance to Nearest Highway	150	**TR**	**Per Capita Income**	**110**
16	SCH	Air Pollution: PM2.5	284	IND	Black	150	**TR**	**Diversity Index**	**104**
17	SCH	Dist Recreational Facility	282	SCH	Food: Dist Produce Market	147	SCH	Mean NDVI	93
18	SCH	All Vehicular Collision Density	280	SCH	Air Pollution: PM2.5	146	SCH	Distance to Nearest Highway	87
19	SCH	Food: Dist Convenience Store	277	SCH	Sinuosity (road)	145	SCH	Sinuosity (road)	86
20	TR	Population Density	276	SCH	Traffic Density	144	SCH	Food: Dist Convenience Store	84
21	SCH	LU: Low Density Development	276	SCH	Dist Recreational Facility	144	TR	Average Time to Work	84
22	TR	% Vacant Housing Units	275	TR	% Vacant Housing Units	143	SCH	Food: Dist Supermarket	84
23	SCH	Food: Dist Small Grocery Store	274	TR	Average Time to Work	142	SCH	Dist Recreational Facility	83
24	SCH	LU Park	274	SCH	Air Pollution: PM10	142	SCH	Food: Dist Produce Market	83
25	SCH	Connectivity Index	274	SCH	Food: Dist Supermarket	141	TR	% Vacant Housing Units	83
26	SCH	Food: Dist Supermarket	272	TR	% Owner Occupied HU	140	SCH	Air Pollution: PM10	83
27	SCH	Air Pollution: PM10	271	***IND***	***Other Race***	***140***	SCH	Traffic Density	82
28	TR	% Owner Occupied HU	270	SCH	Food: Dist Small Grocery Store	139	SCH	LU: Low Density Development	81
29	SCH	Food: Dist Fast Food	266	SCH	Food: Dist Convenience Store	139	SCH	LU Park	81
30	TR	Average Time to Work	262	SCH	Connectivity Index	139	SCH	All Vehicular Collision Density	81
31	SCH	Food: Dist Any Food Venue	261	SCH	LU Park	138	TR	% Owner Occupied HU	81
32	SCH	Air Pollution: NO2	257	SCH	LU: Low Density Development	138	SCH	Food: Dist Small Grocery Store	80
33	SCH	LU High Density Development	234	SCH	All Vehicular Collision Density	136	SCH	Air Pollution: PM2.5	80
34	SCH	PE Teachers Per Student	213	TR	Population Density	134	SCH	Air Pollution: NO2	80
35	TR	Household Growth Rate	198	SCH	Food: Dist Fast Food	132	SCH	Connectivity Index	79
36	SCH	Food: All Venue Prevalence	136	***IND***	***Asian***	132	SCH	Food: Dist Fast Food	79
37	TR	Food: Fast Food Prevalence	112	SCH	Food: Dist Any Food Venue	132	TR	Population Density	78
38	SCH	PE Participation	104	SCH	LU High Density Development	121	SCH	Food: Dist Any Food Venue	75
39	TR	Food: Conv Store Prevalence	88	TR	Household Growth Rate	110	SCH	LU High Density Development	71
40	***IND***	***Asian***	78	SCH	Food: All Venue Prevalence	71	TR	Household Growth Rate	63
41	SCH	LU Agricultural	75	TR	Food: Fast Food Prevalence	63	SCH	Food: All Venue Prevalence	43
42	***IND***	***Black***	64	TR	Food: Conv Store Prevalence	47	TR	Food: Fast Food Prevalence	39
43	TR	Food: Supermarket Prevalence	62	SCH	LU Agricultural	43	TR	Food: Conv Store Prevalence	29
44	SCH	LU Barren	57	TR	Food: Supermarket Prevalence	39	SCH	LU Agricultural	28
45	SCH	LU Wetland	54	SCH	LU Barren	35	TR	Food: Supermarket Prevalence	22
46	SCH	LU Water	54	SCH	LU Wetland	32	SCH	LU Barren	22
47	***IND***	***Other Race***	47	SCH	LU Water	28	SCH	LU Wetland	18
48	TR	Food: Produce Market Prev	42	TR	Food: Produce Market Prev	25	SCH	LU Water	17
49							TR	Food: Produce Market Prev	15

Random Forest variable ranking results by grade of final variable space. Importance refers to the relative contribution to the Random Forest model, which can be interpreted as the change in the model's MSE when the variable is randomly permuted into and out of the model. Variables in green identify those that fall before the importance inflection and are included in the model. Variables in red are those after the "importance inflection" elbow which were forced into the GAMEPHIT model. Abbreviations: SCH: School; TR: Tract; HU: Housing Unit; LU: Land Use; NDVI: Normalized Difference Vegetation Index; Dist: Distance to nearest; IND: individual; PL: Place.

variable set chosen by selecting the non-correlated variables before the second importance inflection from the 124 variable Random Forest results. This includes the top socioeconomic and built environment variables. The long model included 44, 43, and 44 covariates (including individual race, age, gender, and PFT year) for 5th, 7th, and 9th grades, respectively.

3. Results

As part of the correlated variable exclusion process, the 1 km buffer variable consistently had greater influence on obesity than the same variable at 500 m or 250 m buffers. Therefore, the 1 km buffer variable version was used in all cases. School obesity prevalence in our dataset ranged from 0.0% to 75.0% with a median of 19.8% (IQR = 11.5%) and mean of 19.7% (SD = 7.8%) (Table 1.). School percent socioeconomic disadvantaged ranged from 0.0% to 100.0% with a median of 40.2% (IQR = 63.9%) and a mean of 42.7% (SD = 33.8%). School API ranged from 267 to 1000 with a mean and median of 716 and 710, respectively.

3.1. Relative importance of school environment attributes

Table 2 summarizes the results of the machine-learning Random Forest algorithm. Variables are arranged in order of most important at the top to least important at the bottom based on the relative strength of influence. The variables in bold identify those that fall before the importance inflection and are included in the model. The race indicator variables, which were forced into the model are identified in bold italic. Notably, social factors (e.g. English learners, crime) rank consistently higher than physical attributes (land use type, connectivity, greenness and food access) across all grade levels. Only socioeconomic factors were identified before the importance inflection.

3.2. Associations between school environment attributes and obesity

Table 3 presents the logistic regression results with variables standardized. Model results indicate that individual-level characteristics (gender, race, and age) have the largest coefficients. At the local level (school, census tract, county), multiple social attributes have a significant effect. Based on the variable selection process, no built environment attributes were selected and included in the models. Of the local attributes, the school mean academic performance index and census tract mean attained education have the largest inverse effect while the diversity index has the largest positive effect. Percent of students who are English learners or are socioeconomically disadvantaged had a moderate positive association with obesity. Notably, while violent crime ranked high in the variable importance, it has a relatively small coefficient and was not statistically significant for 7th grade. However, crime is positively associated with obesity for 5th and 9th grade students. PE participation has an inverse but small significant effect on obesity for 9th grade, and both the number of PE teachers and accredited teachers per pupil, has a positive, albeit small, effect on obesity.

3.3. Differences between grades

The direction of the associations between the attributes in Table 3 and obesity are consistent across the three models, although for 7th grade, three factors were not statistically significant: violent crime, PE participation, and PE teachers per student. At the local level, associations were consistent; however, there were differences in which variables were selected, as determined by the models, for the three grade levels. This is, in part, due to the exclusion of collinear variables and, in part, due to the importance inflection. For example, socioeconomic disadvantage and English learners were correlated at over 0.7 for 9th grade, but not for 5th or 7th grade.

3.4. Model comparison: mean squared error and unexplained school level variability

While the county-level variability was largely explained by the fixed effects (predictors), a sizeable portion of variability at the school-level was unaccounted for by the model. This suggests that there are other school environment and individual characteristics, which we have not considered, that may contribute to childhood obesity.

Table 4 compares the performance of the final model to three other models by grade: (1) a null model for comparison purposes; (2) a model with only individual covariates and PFT administration year; and (3) a

Table 3
Binomial regression by grade (GAMEPHIT).

Level	Variable	5th Grade OR (95% CI)	7th Grade OR (95% CI)	9th Grade OR (95% CI)
	Constant	0.00 (0.00–0.00)	0.00 (0.00–0.44)	0.00 (0.00–0.00)
Individual	Year of PFT Test	**1.01 (1.01–1.02)**	**1.01 (1.00–1.01)**	**1.02 (1.02–1.03)**
Individual	Female	**0.68 (0.67–0.68)**	**0.72 (0.71–0.72)**	**0.60 (0.60–0.61)**
Individual	Age	**0.86 (0.86–0.87)**	**0.85 (0.84–0.86)**	**0.86 (0.86–0.87)**
Individual	Asian	**0.83 (0.81–0.86)**	**0.71 (0.70–0.73)**	**0.72 (0.70–0.73)**
Individual	Black	**1.26 (1.23–1.29)**	**1.35 (1.33–1.38)**	**1.37 (1.34–1.39)**
Individual	Hispanic	**1.82 (1.80–1.85)**	**1.79 (1.77–1.81)**	**1.70 (1.68–1.72)**
Individual	Other Race	**1.41 (1.36–1.46)**	**1.31 (1.28–1.34)**	**1.29 (1.26–1.32)**
Place	Violent Crime (10–90%ile Range)[1]	**1.01 (1.01–1.02)**	1.01 (1.00–1.02)	**1.04 (1.03–1.07)**
School	Academic Performance Index Score	**0.83 (0.82–0.85)**	**0.83 (0.82–0.85)**	**0.88 (0.86–0.91)**
School	English Learners (10%)	**1.02 (1.01–1.02)**	**1.02 (1.02–1.03)**	**1.02 (1.02–1.03)**
School	SE Disadvantaged (10%)	**1.01 (1.01–1.01)**	**1.01 (1.01–1.01)**	–
School	Fully Credentialed Teachers (10–90%ile Range)[1]	**1.01 (1.00–1.01)**	**1.04 (1.02–1.05)**	**1.01 (1.01–1.02)**
School	PE Participation (10%)	–	1.00 (0.99–1.00)	**0.99 (0.99–1.00)**
School	PE Teachers (/1000 Students)	–	1.00 (1.00–1.01)	**1.01 (1.00–1.02)**
Tract	Diversity Index (10–90%ile Range)[1]	**1.29 (1.25–1.32)**	**1.10 (1.06–1.15)**	**1.08 (1.02–1.14)**
Tract	Mean Education Attained[2]	–	–	**0.92 (0.86–0.97)**
Tract	Per Capita Income ($10 K)	–	**0.96 (0.95–0.96)**	**0.96 (0.94–0.98)**

Note 1: Variables Standardized by the 10–90 Percentile Range.
Violent Crime (Incident per n population): 5th Grade (127); 7th Grade (136); 9th Grade (146).
Full Credentialed Teachers (Teacher per n students): 5th Grade (2.75); 7th Grade (9.28); 9th Grade (20.3).
Note 2: Mean resident education ranges from 1–4 where 1 = less than high school diploma; 2 = high school diploma; 3 = some college; and 4 = college graduate or greater education.
Bold: $p < 0.05$.

Table 4
School variance - one level independent models.

Grade	Mean Squared Error			Random Effect Variance		
	5th	7th	9th	5th	7th	9th
Null Model	0.178	0.157	0.138	0.254	0.216	0.189
Basic Model	0.171	0.152	0.134	0.102	0.109	0.105
Final Model	0.169	0.151	0.133	0.055	0.051	0.055
Long Model	0.169	0.151	0.133	0.050	0.047	0.050

Null Model: normally distributed noise term [0, 1].
Basic Model: Year, Gender, Age, Race Indicator (Asian, Black, Hispanic or Other).
Final Model: Highest importance terms from Random Forest results of final non-correlated variable set, forcing race indicator.
Long Model: Non-correlated top terms (above second importance inflection) from the 124 variable dataset.

full model of all uncorrelated variables above the second importance inflection from the first Random Forest analysis. The MSE shows a conservative improvement between models with progressively more regressors, while the school level random effects variance reduces markedly with the introduction of additional covariates. This suggests that there is a clustered structure to the data and, that while there is moderate improvement of the MSEs, the large reduction of the random effect variance suggests that the covariates are explaining much of the variation in obesity rates. The addition of the individual level variables alone reduced the random effects by a factor of nearly 2.5 for 5th grade, 2.0 for 7th grade, and 1.8 for 9th grade. The introduction of the top socioeconomic covariates, approximately halved the variance of the basic models. Tripling the number of regressors to over 40, however, did very little to improve the models. In this instance, we saw no change in the MSEs and a marginal improvement in the random effect variances.

4. Discussion

This is the first statewide study to look at schools and the school neighborhood as potential targets for environmental public health tracking to identify at-risk populations for the purpose of preventing childhood obesity. Novel methods of machine learning, to better understand the complex mix of data, and a multilevel spatial tool developed for the CDC were utilized. Surveillance systems can be used to identify at-risk populations and to evaluate obesity efforts. Findings support the notion that social and, to a lesser extent physical, environmental attributes of the school setting have an important relationship to childhood obesity. These analyses suggest that the school social environment factors may be especially important for tracking.

Interestingly, our findings are in accordance with the adult literature with respect to social environment. In contrast to the adult literature, the built environment appears to be less important. These findings can be interpreted in several ways: (1) a different relationship exists between adults and the physical environment in comparison to children; (2) the school physical environment is not representative of the home and other physical environments in which children may interact; or (3) the available measures of the school environment do not capture the factors of the physical environment that influence child behaviors while in school.

Many indicators of the social environment were predictive of obesity in the present study and could represent some form of social disadvantage (e.g having fewer credentialed PE teachers). Schools are also places that are influenced by the larger social environment; can attract certain types of policies, teachers, and students; and are places where knowledge, behaviors, and support can be transferred through social networks. Therefore, school social factors can be important to childhood obesity efforts. API was a leading factor and education can be particularly important for health as it may indicate norms/values, skills and self-efficacy that lead to healthier behaviors (Winkleby et al., 1992). It is also possible that the same health behaviors (e.g. nutrition, physical activity, sleep) and school characteristics (e.g. stressors, policies) that are important for API are also important for obesity.

Particular attention was given to ambient air pollution and traffic accident density because they are pervasive modifiable exposures thought to affect weight (Jerrett et al., 2010) that can be mitigated at a macro scale and provide public health co-benefits to the population and have not been previously examined in this scope. There is evidence to suggest that air pollution may modify the risk of obesity through biological and psychological (Sun et al., 2009) and physiological (McConnell et al., 2016) pathways. Also, perceived traffic safety may influence levels of physical activity. A study by Jerrett et al. suggests that higher levels of vehicular traffic are associated with increased BMI in children (Jerrett et al., 2010). The present study suggests that air pollution and traffic around schools may influence childhood obesity; however, based on the Random Forest results, the influence appears to be comparably lower to social factors. Although of lesser importance, for grades 5 and 7, several built environment variables did rank in the top 15 most important, notably NDVI, as a measure of green spaces around the school and traffic density or distance to the nearest large highway, the latter two being proxies for potential traffic risk. Thus, while a secondary influence, measures to calm traffic near schools and introduce green spaces may have a beneficial effect.

4.1. Implications for policy, practice, and research

Obesity surveillance systems in the U.S. monitor trends in BMI, diet, and physical activity (Hoelscher et al., 2017). Many surveillance systems do not monitor contextual factors and other risk factors and only 13 states have school-based surveillance programs that collect BMI (Hoelscher et al., 2017). Schools have been sensitive to some of the concerns about collecting BMI and body composition data (e.g. privacy, stigma, unhealthy behavioral responses) (Hoelscher et al., 2017). For places that do not mandate BMI screening programs, other determinants and risk factors could be collected nationally as these are relevant for policy and practice intervention, and for monitoring health and social disparities.

The findings from the present study suggest that disadvantaged and low academic performing schools are doubly burdened with additional risks, such as higher obesity risk. Monitoring social factors has implications for health equity and for providing a broad understanding of what is needed. For example, it is relatively easy to monitor indicators of school disadvantage, academic performance, and determinants for adequate physical education. Monitoring the number of PE teachers per student provides some understanding of how states might intervene. In addition, academic performance may reflect norms, skills, and self-efficacy that is important for health behaviors, and symmetrically, health behaviors (e.g. nutrition, physical activity, sleep) can be important for academic performance. Disadvantaged schools and communities face more challenges that can include fewer resources and more stressors. Supporting vulnerable schools in a targeted way can be an efficient way to intervene.

The results of the present study demonstrate that there are data relevant to childhood obesity that are not being monitored. However, some findings were not consistent across grades and this needs further study. Additionally, other obesity risk factors could be monitored, such as active transportation programs, presence of vending machines, access to sugar sweetened beverages, open campus policies, and school health policies. Improvements to the California tracking system could include collecting yearly height and weight data starting from an earlier age The State of California issues student IDs to all students in the California public school system, which are ideal for longitudinal studies and relating multiple databases maintained at the individual level by the state. Providing these linkages can be useful for monitoring and studying changes over time to improve our understanding of modifiable environmental risk factors for childhood obesity.

4.2. Limitations

This study used numerous environmental measures and statewide data for indicators of childhood obesity. Despite this, there are some limitations. First is the lack of longitudinal data. Without an ability to follow the students through changing environments and changing weight status, we are limited to the drawbacks of cross-sectional data, which limits any causal conclusions.

Second, there are additional factors that were not included in the present study. Some features of the within-school physical environment were not available (e.g. quality of physical activity facilities, the quality of the school cafeteria food). The family and residential neighborhood environment were not included in this study. It is possible that some of social environment indicators are also correlated with home environments. However, it is also possible that home neighborhood environments differ from school environments. For example, schools may be in areas where land is cheaper and where permitted by zoning laws; they may be closer to major roads and highways and areas of higher traffic. Homes, on the other hand, may be in areas with lower traffic, a perceived safer environment, and low density development. While children spend a significant portion of their day at school, the home environment is likely to also be a contributor to their diet and physical activity.

Third, these findings may not be generalizable to all schools in the U.S. In addition, not all public schools or students participated in the FITNESSGRAM®. Information bias may be present in multiple forms. For example, wealthier schools may have employed trained individuals to conduct the tests, while other schools may not have the resources to do the same.

5. Conclusion

This is the first state-wide study to look at schools and the school neighborhood as potential targets for environmental public health tracking to identify the at-risk populations for the purpose of addressing childhood obesity. There has been growing interest in focusing on the physical environment to decrease obesity. Our findings suggest that social aspects of the school environment may be more important for environmental public health tracking than built environment variables.

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Declaration of interest

Dr. Ortega Hinojosa contributed to this paper while he was a student the University of California, Berkeley and employee of IMPAQ International, LLC.

Dr. MacLeod contributed to this paper while an employee of the University of California, Los Angeles.

Dr. Balmes contributed to this paper as a faculty member of the University of California, Berkeley and the University of California, San Francisco.

Dr. Jerrett contributed to this paper as a faculty member of the University of California, Berkeley and the University of California, Los Angeles.

The authors have no conflicts of financial interest to report.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.envres.2018.04.022.

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Krewski D., Hughes E.. Research Report 140 Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality Appendix B. Algorithmic Description of the Cox Poisson Program APPENDIX B: Algorithmic Description of the Cox-Poisson Program Algorithmic Description of the Cox-Poisson Program. 〈https://www.healtheffects.org/system/files/KrewskiAppendixB.pdf〉.

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