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Association between substandard classroom ventilation rates and students' academic achievement

Abstract This study focuses on the relationship between classroom ventilation rates and academic achievement. One hundred elementary schools of two school districts in the southwest United States were included in the study. Ventilation rates were estimated from fifth-grade classrooms (one per school) using CO_2 concentrations measured during occupied school days. In addition, standardized test scores and background data related to students in the classrooms studied were obtained from the districts. Of 100 classrooms, 87 had ventilation rates below recommended guidelines based on ASHRAE Standard 62 as of 2004. There is a linear association between classroom ventilation rates and students' academic achievement within the range of 0.9–7.1 l/s per person. For every unit (1 l/s per person) increase in the ventilation rate within that range, the proportion of students passing standardized test (i.e., scoring satisfactory or above) is expected to increase by 2.9% (95%CI 0.9–4.8%) for math and 2.7% (0.5–4.9%) for reading. The linear relationship observed may level off or change direction with higher ventilation rates, but given the limited number of observations, we were unable to test this hypothesis. A larger sample size is needed for estimating the effect of classroom ventilation rates higher than 7.1 l/s per person on academic achievement.

U. Haverinen-Shaughnessy[1,2], D. J. Moschandreas[3], R. J. Shaughnessy[1]

[1]The University of Tulsa, Indoor Air Program, Tulsa, OK, USA, [2]National Institute for Health and Welfare, Environmental Health Department, Kuopio, Finland, [3]Illinois Institute of Technology, Department of Civil, Architectural and Environmental Engineering, Chicago, IL, USA

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Dr. R. Shaughnessy
The University of Tulsa, Indoor Air Program
600 S College Ave, Henneke Bld, Room 212
Tulsa, OK 74104-3189, USA
Tel.: +1 918 230 3908
Fax: +1 918 631 3291
e-mail: rjstulsau@aol.com

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Practical Implications

The results of this study suggest that increasing the ventilation rates toward recommended guideline ventilation rates in classrooms should translate into improved academic achievement of students. More studies are needed to fully understand the relationships between ventilation rate, other indoor environmental quality parameters, and their effects on students' health and achievement. Achieving the recommended guidelines and pursuing better understanding of the underlying relationships would ultimately support both sustainable and productive school environments for students and personnel.

Introduction

Academic achievement is widely studied by education and social science scholars. A recent literature search (http://www.eric.ed.gov) of 'academic achievement' (over 24,000 peer-reviewed articles) reveals that academic achievement is associated with a variety of socioeconomic status (SES) variables including parents' education, family income, ethnicity, and home conditions (Sirin, 2005; Peng and Wright, 1994); language proficiency and mobility (Ingersoll et al., 1988, Saville-Troike, 1984); teacher qualifications (Rivkin et al., 2005; Nye et al., 2000; Sanders and Rivers, 1996); classroom composition, peer relations, and personal qualities including intelligence, academic inclination, and motivation (Fuligni, 1997; Leiter, 1983). Although it has been suggested that the quality of schools has major influences on students' learning (Heyneman and Loxley, 1983), none of these studies has included ventilation or other pertinent classroom indoor environmental quality (IEQ) parameters (such as air pollution, thermal conditions, noise and/or light) among the parameters used to predict academic achievement.

Environmental scientists reason that better health, decreased absenteeism, increased performance and productivity, and operational cost reduction are among the benefits of improved IEQ in schools (Johnson, 2005; Schulte et al., 2005; Shendell et al., 2004; Smedje and Norbäck, 2000; Leach, 1997). Intuitively, these benefits are believed to be correct, yet research on better defining the outcomes is sparse.

A basic step to enhancing IEQ in schools is providing adequate ventilation by ensuring compliance with the recommended guidelines/standards. Low ventilation rates lead to unpleasant, 'stuffy' air, elevated concentrations of air pollutants (such as microbes, particles, and volatile organic compounds), and consequent potentially decreased IEQ, adverse health effects, and students' absenteeism. These effects may reduce students' learning potential, and lead to decreased academic performance/achievement among students. Several studies have established that ventilation rates are commonly below recommended levels in schools (e.g., Daisey et al., 2003). However, studies linking IEQ and ventilation in the classrooms directly to student performance are limited (Mendell and Heath, 2005).

A few studies suggest that low air exchange rates in classrooms play an important role in student performance (Wargocki and Wyon, 2006, 2007), yet such conclusions are limited by: (i) experimental design and/or sample size, which is usually too small to reach definitive conclusions and (ii) methods used to evaluate student performance, which is assessed by response speed, error rate, and other short-term tests that may or may not be good surrogates of performance.

Academic performance reflects long-term achievement assessed by standardized state and/or nation-wide tests. Group level performance over a long time-span (e.g., over an academic year) is measured by the percentage of students scoring proficient or above on the standard tests administered annually. In the education field, this measure is often referred to as academic achievement. In this respect, our studies represent the first attempt to associate classroom ventilation rates with academic achievement.

The database employed in this paper includes classroom ventilation rates from a total of one hundred schools in two districts in the southwest United States. The region has a continental climate with relatively cold winters (annual heating degree days around 3700) and hot summers (annual cooling degree days around 1900). Normal daily mean temperatures range from 37°F (3°C) in January to 82°F (28°C) in July. Average annual precipitation is about 36 in (90 cm), and snowfall averages 9 in (23 cm) a year.

Preliminary results of the two school districts have been reported separately (Shaughnessy et al., 2006, 2007). Such conclusions were constrained by the sample size that did not provide sufficient statistical power for the analyses. To provide more statistical power, merging of the datasets was undertaken. In addition to the ventilation data, standardized, statewide, achievement test results in mathematics and reading, administered to the students on a yearly basis, and data representing pertinent facts of students' background in the specific classrooms studied were obtained from the districts. The objective is to study the association between ventilation rates and academic achievement of fifth graders.

Material and methods

Fifth-grade classrooms, in 104 elementary schools (one classroom per school), were monitored for carbon dioxide (CO_2) concentrations using infrared-based data-logging measurement equipment during occupied hours of a school day. The CO_2 monitors used were calibrated according to the instruction manual on a weekly basis and intercalibrated (i.e., compared with each other). The continuous data logging lasted a minimum of 1 day in each classroom and it took place during the winter/spring months of the school year. Other IEQ parameters monitored included temperature, relative humidity, carbon monoxide, and in one of the school districts, particle counts. The results of these other IEQ measurements will be reported elsewhere.

Classrooms were monitored under 'closed' conditions, keeping windows and doors closed as best possible during the occupied hours. This was performed in an attempt to minimize window and door influences. Heating, ventilation, and air conditioning (HVAC) systems were operated with fans in the 'on' position during the monitoring period. Recognizing that seasonal times of the year will have some impact on ventilation rates, the closed classroom conditions were instilled to provide a better estimate of ventilation rates (based on mechanical system introduction of outdoor air) during the brief measurement period. The data loggers recorded data in 5-min increments throughout the day. Range of monitors was 0–6000 ppm, with an accuracy of $\pm 3\%$ of the reading or ± 50 ppm whichever is greater.

The maximum indoor CO_2 concentrations measured in each school ranged from 661 to 6000 ppm (mean 1779, s.d. 852), while the outdoor concentrations ranged from 328 to 442 ppm (mean 375, s.d. 29). The CO_2 concentrations were used to estimate ventilation rates in the class rooms (ASTM 2007, Bearg, 1993) using mass-balance model.

Calculation of a CO_2 source generation, used in our analyses, was based on several factors such as age, body weight and surface area, mass, and level of physical activity (light activity) (USEPA 1997). The CO_2 generation rates used were 0.0043 l/s per person for students and 0.0052 l/s per person for teachers (USEPA 1997, Tudor-Locke et al., 2009; Persily, 1997). It was assumed that CO_2 concentrations had reached steady state (C_{eq}) in the classrooms. The peak concentration of CO_2 recorded during the day was used as the steady-state value of CO_2.

The mean class size was 21, ranging from 12 to 45 students per classroom, although 95% of the classrooms had 15–30 students. If the estimated ventilation rate is assumed to stay constant at other times, but the occupancy outside the test period may change, then the ventilation rate per occupant would be different at other times. Therefore, we noted the occupancy of each classroom during the test period and also over the school year and adjusted the estimated ventilation rate per person to reflect occupancy conditions during the school year.

In addition to our primary approach of estimating ventilation rates based on the steady-state approach (using peak values of CO_2 as input), a 'buildup analysis' approach was used for comparison purposes. The buildup method is based on the transient analysis of CO_2 as the concentration increases or builds up in the morning. Whereas these types of data were not available for many classrooms because of occupancy variance and initial placement time of the monitors, a subset of 15 schools was extracted for further review and analyzed based on the buildup of CO_2 concentrations (typically between 8:30 AM and 10:30 AM). The single-zone mass-balance was applied, and a non-linear regression technique was used to obtain CO_2 values and the ventilation rates with confidence intervals.

All of the studied classrooms were equipped with locally controlled mechanical HVAC systems. None of the classrooms relied on natural ventilation alone for the introduction of outdoor air. The ventilation systems primarily consisted of single-zone room units (i.e., residential style up flow furnace-type systems, unit ventilators, roof top units serving one room only, and fan coil units), which are appropriate for the method of approximating ventilation rates using CO_2 concentrations. The volume of outdoor air determined by direct measurements at the air handler, which is a different method for estimating ventilation rates, was not utilized because of the variability in type of HVAC systems in the classrooms.

In addition to ventilation data recorded, we obtained standardized test scores and background data related to students in the specific classrooms studied. Fifth graders were selected because they are generally assigned to one classroom and are required to take standardized tests each spring.

Test scores are based on a criterion-referenced testing program, which compare a student's performance with performance standards established by the State Board of Education. These standards identify specific levels of performance required on each test. The standards-based criteria are directly aligned to the State's legislatively mandated core curriculum. In the content areas of Mathematics, Reading, Science, Social Studies, and Writing, a student's test performance is reported according to one of four performance levels: Unsatisfactory, Limited Knowledge, Satisfactory, and Advanced.

Each year, students in Grade 5 take Multiple-Choice tests. Each Multiple-Choice subject test is divided into two separate sections. These two sections of the test may be administered on the same day with a break given between the sections or on consecutive days. Individual test scores for each student, as well as detailed group summary reports, are sent back to the schools.

Each school within the district takes each test at the same time. For the year of classroom sampling (spring 2004 in District #1 and spring 2006 in District #2), the percent of students scoring satisfactory or above in math and reading tests was selected as the primary metric of academic achievement used in the study. Other pertinent classroom level information included mobility rate, percent limited English (English language learners), free lunch program participants (economically disadvantaged), and gifted enrollment. Student level information was not available for this study.

Mobility rate is a measure of how many students are transferring in and out of a school. Percent limited English accounts for students who come from an environment where a language other than English has had a significant impact on the student's level of English language proficiency, or those students who are migratory, whose native language is other than English. Percent free lunch participation accounts for students eligible to participate in the free lunch program and it is therefore considered an indicator of SES. Percent gifted enrollment reflects the portion of students identified as having demonstrated potential abilities of high performance.

The database was analyzed using SPSS statistical package version 14.0 (SPSS Inc., Chicago, IL, USA), ProULC version 4.00.02 (US EPA, Atlanta, GA, USA), and R software version 2.2.1 (The R Foundation for Statistical Computing, Vienna, Austria). Of 104 schools/observations, two were in error (conditions unstable in the classroom during monitoring) and omitted from further analyses. In addition, one school was omitted because of different student profile (all students had limited English proficiency), and one school was omitted because data screening revealed it being an outlier based on Rosner's test. Hence, the final sample included a total of 100 schools. Before merging the data from the two districts, we tested the null hypothesis on whether the two data sets came from the same population. It was concluded that the two databases can be merged; it was also noted the two districts are in the same state, they use the same tests to evaluate students' academic achievement, and the IEQ parameters were measured in the same way by the same research team. The dependent variables (math and reading scores) were normally distributed in the merged data of the two districts. Possible differences between the two districts (e.g., in socioeconomic factors, time span in data collection) were accounted for in the analyses.

Initially, all ventilation data from the 100 schools were scrutinized. Bivariate associations between ventilation rate and test scores were assessed using simple linear regression. To take into account possible non-linear effects, further analyses were made using penalized thin-plate regression splines in the generalized additive models framework. Modeling was implemented using R software and mgcv 1.3-7 procedure. If the estimated degree of freedom for the smooth term was < 1.5, the term was considered to be linear. In addition, residual and influence statistics were performed based on the full data analyses.

Subsequent analyses were performed with a filtered database that included only classrooms with ventilation rates equal to or < 7.1 l/s per person (i.e., ASHRAE recommended minimum ventilation rate at the time of the investigation). Multiple linear regression modeling (MLR) was performed, including known socioeconomic variables and ventilation rate as independent variables. Forward, backward elimination, and stepwise variable selection procedures were employed to address multi-collinearity of correlated independent variables in MLR models and to obtain simple models containing fewer independent variables. In these models, P-to-enter was specified as 0.05 and P-to-remove as 0.10.

Results

As shown in Figure 1, the mean ventilation rate of the merged database is 4.25 l/s per person (range 0.90–11.74, 95%CI for mean ± 0.45 l/s per person), and the median is 3.55 l/s per person, which corresponds to approximately half of the minimum recommended ventilation rate of 7.1 l/s per person at the time of the investigation (ASHRAE 2004).

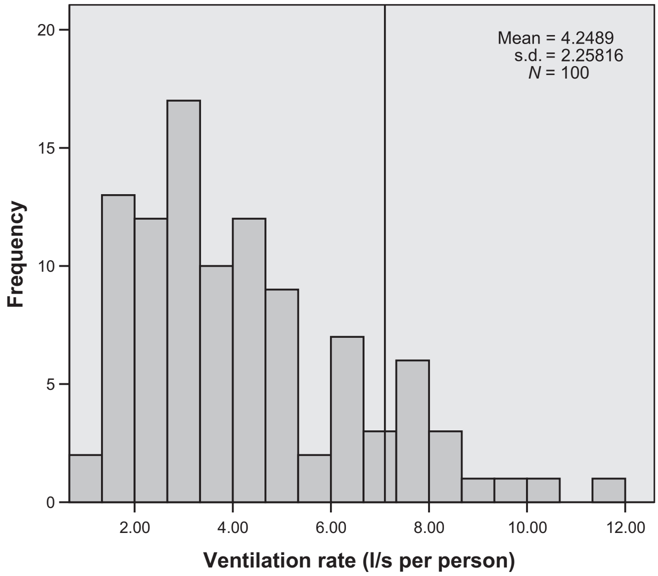

Fig. 1 Ventilation rate distribution (vertical line corresponds to ASHRAE recommended minimum)

Ventilation rates shown in Figure 1 were estimated based on the steady-state approach using peak carbon dioxide concentration values recorded in the classrooms. For comparison purposes, in the subsequent buildup analyses, the mean of the peak CO_2 values from the 15 school subset was 1881 ppm (95%CI for mean ± 354 ppm), while the mean from the remaining 85 schools was 1804 ppm (95%CI for mean ± 157 ppm), revealing the data sets being similar.

Based on Shapiro–Wilk's test of normality, the data related to CO_2 are normally distributed, whereas data related to ventilation rate are not normally distributed. Peak CO_2 concentration values observed and values predicted based on the buildup analyses are significantly correlated (Pearson correlation 0.886) and there are no significant differences between the mean values ($P = 0.290$) based on paired samples *t*-test.

Observed peak CO_2 (CO_2peak) is plotted against predicted CO_2 (CO_2pred) based on the buildup analyses in Figure 2. CO_2peak values appear to be lower especially for predicted values > 2000 ppm. This result is consistent with the observation that at lower ventilation rates, the peak approach may underpredict

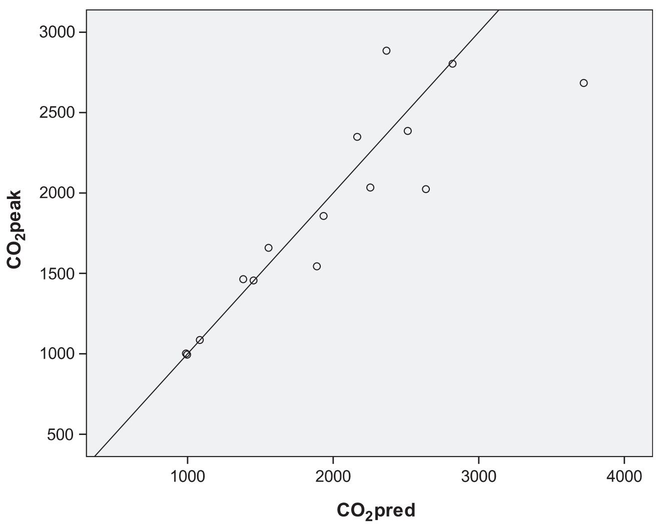

Fig. 2 CO_2peak plotted against CO_2pred in a sample of 15 schools

the true steady-state CO_2 value. The mean difference between CO_2peak and CO_2pred is 102 ppm. Mean 95%CI for CO_2pred is 279 ppm (17–1347 ppm). In most cases, CO_2peak is within 95%CI for CO_2pred.

Also ventilation rates estimated based on CO_2peak and CO_2pred are significantly correlated (Pearson correlation 0.785; Spearman's correlation 0.726). The mean difference between the ventilation rate estimates is 1.2 l/s per person (0.0–4.8 l/s per person), and the median difference is 0.8 l/s per person. There is no statistically significant difference between ventilation rates based on paired samples *t*-test ($P = 0.277$) or Wilcoxon Signed-Ranks test ($P = 0.691$). Mean 95%CI for predicted ventilation rates is 1.2 l/s per person (0.2–2.9 l/s per person), and median 95%CI is 1.0 l/s per person (0.1–2.9 l/s per person), correspondingly.

Simple linear regression coefficients for associations between ventilation rate and both math and reading scores in the full merged database (N = 100) were 1.018 (95%CI −0.493 to 2.528, P = 0.184) for math and 1.311 (95%CI −0.507 to 3.728, P = 0.156) for reading, correspondingly. Therefore, the associations were not statistically significant, which could also indicate insufficient statistical power.

Figure 3 shows the fitted (crude) curves with 95% confidence intervals. Utilizing the full data set (100 schools) results in a bell-shaped curve, however, the uncertainty increases particularly with higher ventilation rates. There is a point above which the upper CI corresponds with continuous increase, and the lower CI corresponds with decrease, and the P-values of the smooth terms are >0.1. Using filtered data, i.e., ventilation rate equal to or <7.1 l/s per person (N = 87), the fitted curves become linear and the P-values are <0.05.

Figures 4 and 5 illustrate the results of residual and influence statistics. Figure 4 shows leverage values plotted against ventilation rate. Leverage values vary between 0 and 1 and measure how much influence a single observation has on a regression model. The mean leverage value is approximated by $2/N$, i.e., in this case 0.02. Ventilation rates above 7.1 l/s per person are all (asymmetrically) above the mean value. Standardized differences in fit values are plotted in Figure 5. The values correspond with the change in the predicted value that results from the exclusion of a particular case. Suspect values are those which in

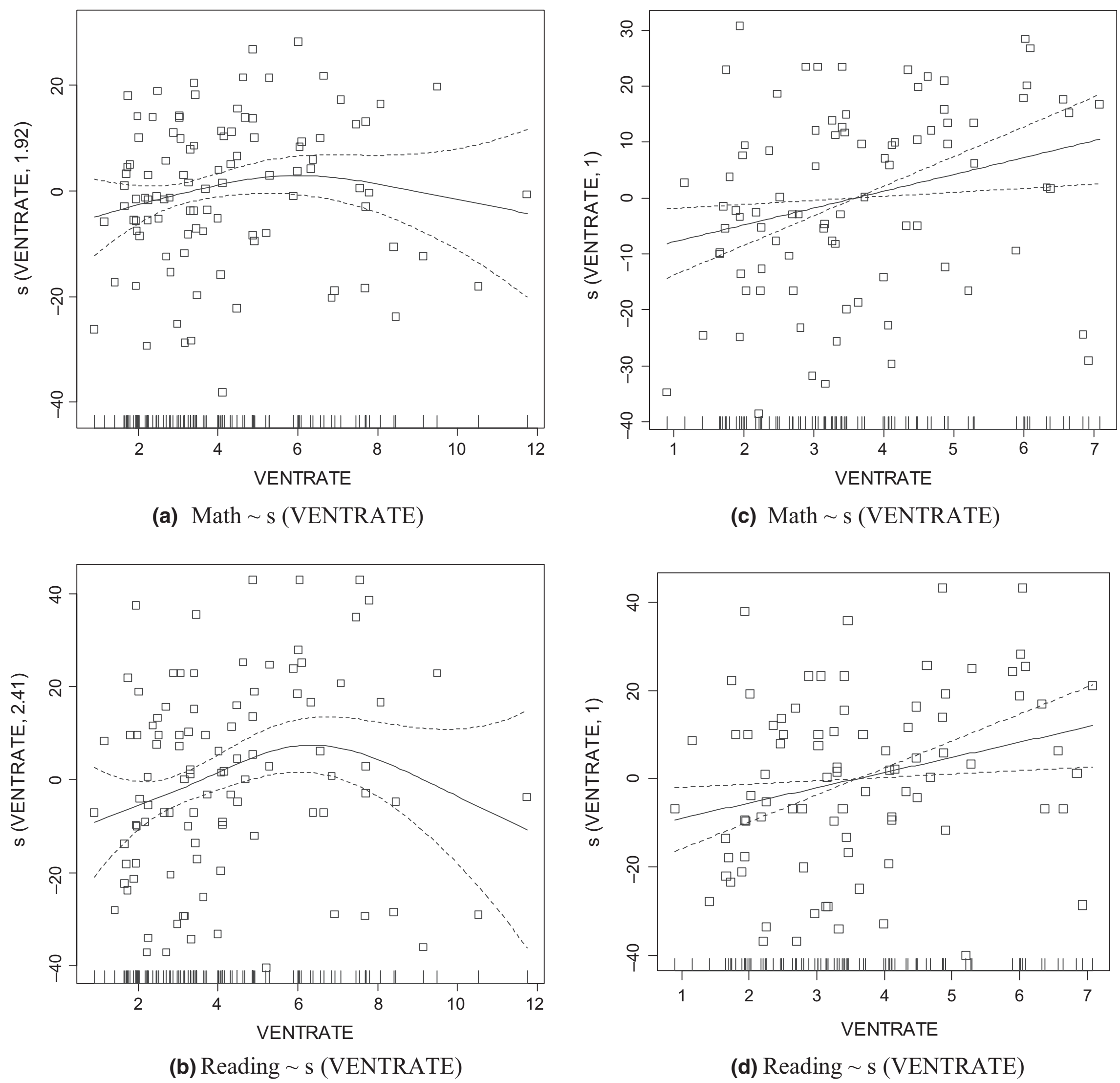

Fig. 3 Fitted curves for the (crude) association between ventilation rate (VENTRATE) and math (a, d) and reading (b, c) scores. Curves (a) and (b) correspond with full data set of 100 schools, whereas (c) and (d) correspond with filtered dataset of 87 schools (ventilation rates below 7.1 l/s per person)

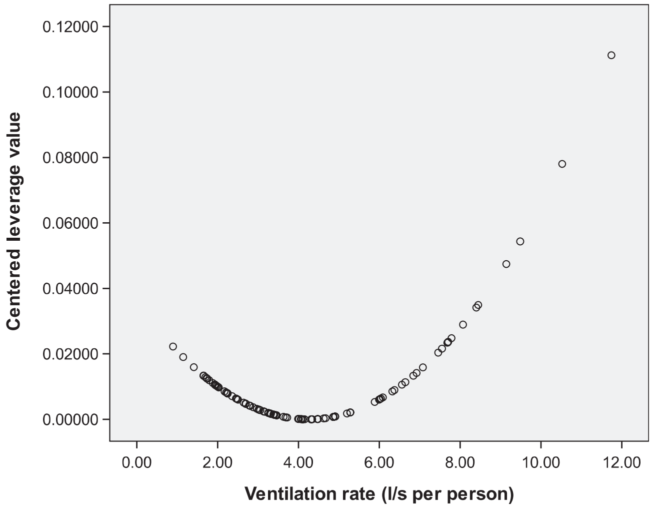

Fig. 4 Leverage values plotted against ventilation rates

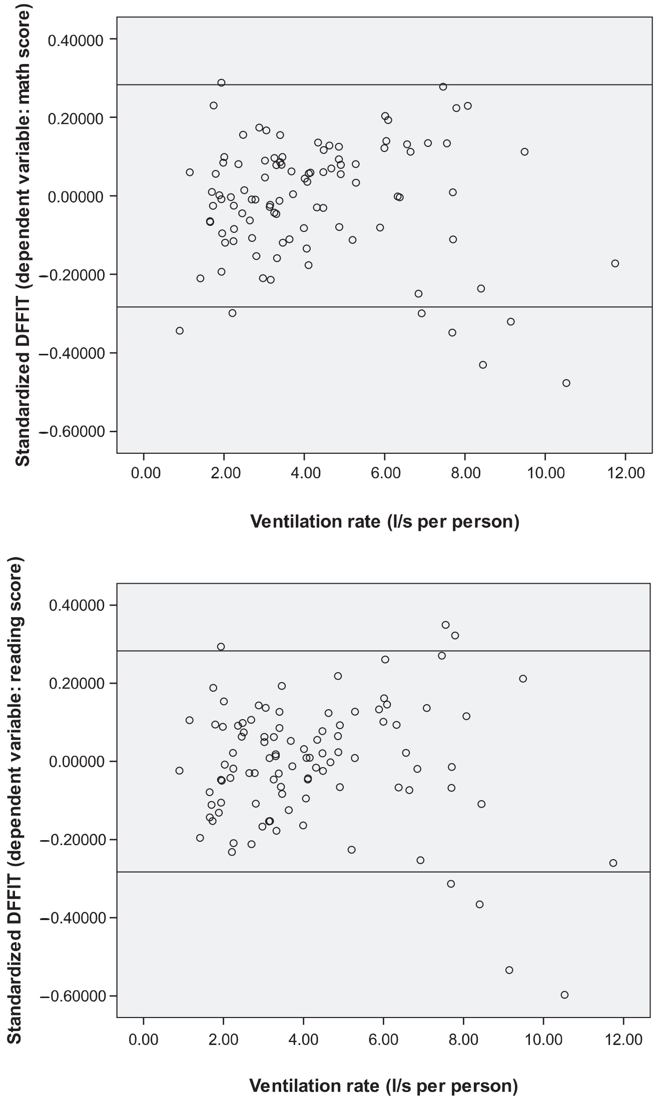

Fig. 5 Standardized difference in fit value (Standardized DFFIT) plotted against ventilation rates. Standardized DFFIT represents the change in the predicted value that results from the exclusion of a particular case (i.e., the larger the absolute value the higher the influence)

absolute value exceed two times the square root of p/N, where p is the number of parameters in the model, and N is the number of cases. Horizontal lines in Figure 3 correspond to these values (±0.2828). These results supported analyses using filtered data.

Following simple linear regression, analyses associate substandard ventilation rates with math (coefficient 3.012, P = 0.010) and reading (coefficient 3.441, P = 0.012) scores significantly. The proportion of total variability in the response variable accounted for by each model is 0.072 and 0.075, respectively.

Multiple linear models include the data source term ('district') as well as student background/SES variables (i.e., mobility rate, percent limited English, free lunch participation, and gifted enrollment) in the models. Although there were significant correlations between the SES variables, there were no significant correlations between any of these variables and ventilation rate, see Table 1.

Full MLR models include all known background/SES variables and ventilation rate as independent variables, see Table 2. The model-adjusted R^2 values, which allow comparisons to be made between models with different number of predictor variables, are 0.374 for math and 0.427 for reading. Models that exclude ventilation rate as an independent variable, thus including only data source ('district') and background/SES variables, result in a reduced adjusted R^2 values of 0.318 (math) and 0.392 (reading). Partial R^2 between ventilation rate and the test scores in the full model are 0.094 (math) and 0.070 (reading), respectively, see Figure 6.

For reading, use of forward, backward elimination, and stepwise variable selection procedures each led to the same set of variables, including the district, % free lunch, % gifted enrollment, and ventilation rate (Table 2). For math, backward elimination procedure led to selection of the district, mobility rate, % limited English, % free lunch, and ventilation rate; whereas stepwise and forward procedures led to variables including mobility rate, % gifted enrollment, and ventilation rate. The later model is presented in Table 2, because it contains fewer variables. Adjusted R^2 of these models are 0.270 for math and 0.428 for reading, and the proportions of variance explained by ventilation rate are 0.054 and 0.067, respectively.

Background information on male/female ratio, attendance rate, ethnicity (percentage of White, Black, Hispanic, American Indians, and Asian students), and information on teacher qualifications (number of certified teachers in the school, their average years of experience, and degrees earned) were obtained from one of the districts. The sample size of schools with

Table 1 Non-parametric (Spearman's rho) correlations between full model variables

	Math score	Reading score	% Free lunch	% Limited English	Mobility rate	% Gifted enrollment	Ventilation rate
Math score	1.000	0.761[a]	−0.140	−0.050	−0.383[a]	0.476[a]	0.309[a]
Reading score	0.761[a]	1.000	−0.231[b]	−0.202	−0.320[a]	0.526[a]	0.281[a]
% Free lunch	−0.140	−0.231[b]	1.000	0.183	0.001	−0.210	0.188
% Limited English	−0.050	−0.202	0.183	1.000	−0.013	−0.085	−0.140
Mobility rate	−0.383[a]	−0.320[a]	0.001	−0.013	1.000	−0.371[a]	−0.106
% Gifted enrollment	0.476[a]	0.526[a]	−0.210	−0.085	−0.371[a]	1.000	0.195
Ventilation rate	0.309[a]	0.281[a]	0.188	−0.140	−0.106	0.195	1.000

[a]Correlation is significant at the 0.01 level (two-tailed).
[b]Correlation is significant at the 0.05 level (two-tailed).

Table 2 Multiple linear regression models for math and reading scores (N = 87)

1 Crude model 2 Full model 3 Reduced model	Unstandardized coefficients		Standardized coefficients		
	B	s.e.	Beta	*T*	Significance
Dependent variable: math					
1					
(Constant)	55.698	4.479		12.436	0.000
Ventilation rate	3.012	1.146	0.274	2.629	0.010
2					
(Constant)	66.662	8.158		8.172	0.000
District	12.812	3.560	0.381	3.599	0.001
% Free lunch	−0.364	0.103	−0.402	−3.528	0.001
% Limited English	0.178	0.090	0.191	1.977	0.051
% Gifted enrollment	0.215	0.157	0.146	1.369	0.175
Mobility rate	−0.255	0.121	−0.196	−2.102	0.039
Ventilation rate	2.850	0.990	0.260	2.879	0.005
3					
(Constant)	61.597	5.421		11.363	0.000
Mobility rate	−0.318	0.127	−0.245	−2.500	0.014
% Gifted enrollment	0.489	0.146	0.332	3.344	0.001
Ventilation rate	2.229	1.026	0.203	2.172	0.033
Dependent variable: reading					
1					
(Constant)	44.376	5.228		8.489	0.000
Ventilation rate	3.441	1.337	0.269	2.573	0.012
2					
(Constant)	50.766	9.095		5.582	0.000
District	13.374	3.969	0.342	3.369	0.001
% Free lunch	−0.330	0.115	−0.313	−2.866	0.005
% Limited English	0.029	0.100	0.026	0.285	0.776
% Gifted enrollment	0.536	0.175	0.311	3.053	0.003
Mobility rate	−0.237	0.142	−0.157	−1.666	0.100
Ventilation rate	2.711	1.104	0.212	2.456	0.016
3					
(Constant)	44.980	7.849		5.731	0.000
% Gifted enrollment	0.603	0.168	0.351	3.592	0.001
District	13.454	3.759	0.344	3.579	0.001
% Free lunch	−0.312	0.107	−0.295	−2.920	0.005
Ventilation rate	2.655	1.097	0.207	2.419	0.018

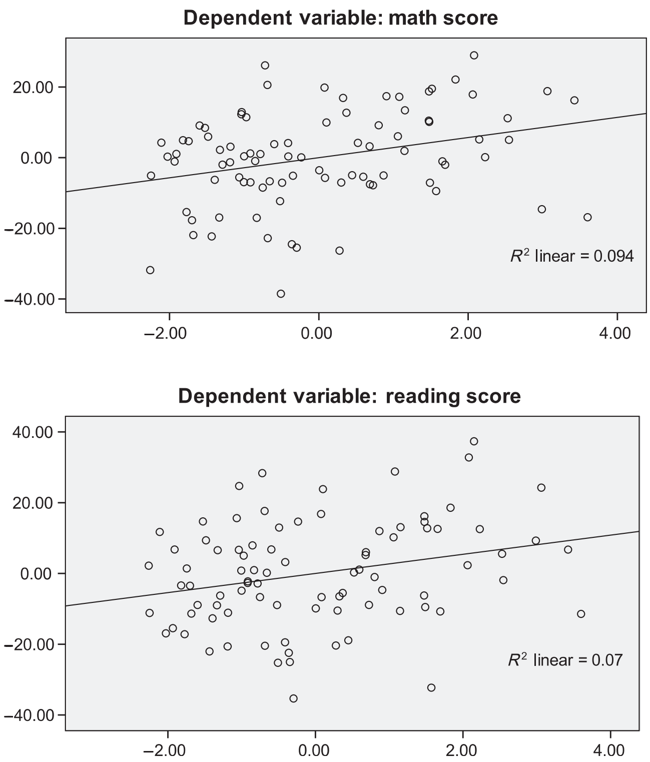

Fig. 6 Partial regression plots for the linear association between math and reading scores and ventilation rate in the full models, showing the correct strength of the linear relationship between the response variable and Xi, i.e., ventilation rate (note: x-axis does not represent the actual Xi). Partial R^2-values are 0.135 (math) and 0.124 (reading) for the district; 0.135 (math) and 0.093 (reading) for % free lunch; 0.047 (math) and 0.001 (reading) for % limited English; 0.052 (math) and 0.020 (reading) for mobility rate; and 0.023 (math) and 0.104 (reading) for % gifted enrollment

ventilation rates below 7.1 l/s per person was n = 47. The stepwise procedure tested the effect of the additional variables on full models and selects variables that significantly improve the models' prediction. For math, the only variable selected was % Asian students, whereas for reading, % white students and number of certified teachers were selected (Table 3). As a result, standardized R^2 of the model increased from 0.320 to 0.377 for math and from 0.262 to 0.421 for reading. Whereas adding these variables in the models naturally increased R^2, they had a little effect on the partial R^2, i.e., proportion of variance explained by ventilation rate.

Class size is the one factor that may be related to both ventilation rate (the more pupils in the classroom, the more outdoor air is required for adequate ventilation)

Table 3 Multiple linear regression models for math and reading scores in District 1 (*N* = 47)

1 Full model 2 Stepwise model	Unstandardized coefficients *B*	s.e.	Standardized coefficients Beta	*T*	Significance
Dependent variable: math					
1					
(Constant)	101.790	15.562		6.541	0.000
% Free lunch	−0.650	0.167	−0.678	−3.892	0.000
% Limited English	0.332	0.138	0.340	2.402	0.021
% Gifted enrollment	−0.186	0.301	−0.105	−0.616	0.541
Mobility rate	−0.384	0.219	−0.270	−1.757	0.086
Ventilation rate	3.206	1.453	0.297	2.207	0.033
2					
(Constant)	106.115	15.036		7.057	0.000
% Free lunch	−0.695	0.161	−0.725	−4.308	0.000
% Limited English	0.371	0.133	0.380	2.780	0.008
% Gifted enrollment	−0.185	0.289	−0.104	−0.642	0.524
Mobility rate	−0.337	0.211	−0.237	−1.600	0.117
Ventilation rate	2.939	1.397	0.273	2.105	0.042
% Asian	−0.821	0.379	−0.260	−2.169	0.036
Dependent variable: reading					
1					
(Constant)	79.663	19.660		4.052	0.000
% Free lunch	−0.506	0.211	−0.436	−2.401	0.021
% Limited English	0.206	0.174	0.174	1.180	0.245
% Gifted enrollment	0.502	0.381	0.234	1.320	0.194
Mobility rate	−0.281	0.276	−0.163	−1.018	0.315
Ventilation rate	1.825	1.835	0.140	0.994	0.326
2					
(Constant)	67.871	21.200		3.202	0.003
% Free lunch	−0.316	0.209	−0.272	−1.515	0.138
% Limited English	0.290	0.184	0.245	1.572	0.124
% Gifted enrollment	0.099	0.359	0.046	0.276	0.784
Mobility rate	−0.245	0.245	−0.142	−0.999	0.324
Ventilation rate	2.465	1.653	0.189	1.491	0.144
% White	0.555	0.183	0.477	3.026	0.004
No. of certified teachers	−1.056	0.445	−0.329	−2.374	0.023

and academic achievement (Koth et al., 2008; Milesi and Gamoran, 2006). However, the mechanisms as to how the class size relates to higher achievement have not been clear (Nye et al., 2000). We examined the effect of class size on the relationships between ventilation rate and test scores.

The correlation between ventilation rates and number of students in the classrooms was insignificant, indicating that the classrooms with low ventilation rates were not necessarily the ones with large class size. Moreover, including the number of students in the MLR models did not change the ventilation rate coefficients substantively when compared to the simple linear model ($\leq 3\%$ change), and the proportions of variance explained by ventilation rate were, in fact, slightly increased. Running the variable selection procedure with the number of students included did not change the variables selected in the final models (data not shown).

Teacher effect has been estimated to be the single most dominant school-related factor affecting student academic achievement. A study by Sanders and Rivers (1996) estimated a 7–8% difference in mean scores of fifth-grade math achievement between consistently high and consistently low teacher effectiveness over a 3-year sequence. Our study included a subset of data on teacher qualifications, but they did not correlate with test scores. In MLR analyses, the number of certified teachers had a negative effect on reading scores. Yet, it has been established that only a small portion of teacher effectiveness is explained by such indices as teacher experience or education (Rivkin et al., 2005). However, it is plausible that substandard ventilation may also decrease teacher effectiveness, analogous to the effects that have been observed among office workers (Seppänen et al., 2005).

Discussion

The importance of academic performance is never questioned, but reaching consensus on its measurement is elusive. In the environmental field, various indicators have been used to characterize student performance including cognitive tests, productivity (such as speed of completing a task), and numerical or language tasks. On the other hand, experts in the education field question if these metrics that focus on short-term tasks truly measure performance and are using term academic achievement in connection with tests that assess long-term classroom knowledge. In our studies, we have used the terms academic performance and achievement interchangeably, adopting a definition used by several states, which is based on results from state-wide, annually performed, curriculum-based tests in various academic areas, including reading and mathematics.

The results of this study indicate that the amount of outdoor air provided to the rooms was in the majority of cases less than the current standard. Whereas these findings are consistent with other studies found in the literature (Daisey et al., 2003), it is important to recognize the limitations in using the steady-state approach to estimating the ventilation rates using peak CO_2 concentration values recorded in the classrooms, being that steady state was not always achieved. In classrooms with very low ventilation rates, it may take an extended occupancy to reach steady state. Hence, the peak CO_2 measurement technique has built in uncertainties that may vary depending on the ventilation rate itself and the number of restricted hours that occupants remain within the space.

A basic challenge is that any CO_2 approach utilized for the estimation of ventilation rates (with children in the classroom) will be affected by levels of activity that will typically vary throughout a given school day. In addition, classroom environments are difficult to characterize because of the activities that typically are non-stop in fifth-grade classrooms and will vary anywhere from children engaging in activities similar to exercise (4 met), to quiet at desks (1.2 met), to sleeping (0.75–1.0 met). Therefore, there will always be uncertainties related to the individual approach selected. In this paper, authors utilized the source term calculated from literature data based on age, body weight and surface area, mass, and estimated level of physical activity of the children.

The buildup analysis approach was applied on a subset of the carbon dioxide data to provide an alternative representation of the best-estimate steady-state carbon dioxide levels and associated ventilation rates. These further analyses were primarily conducted to provide an estimate of the uncertainties in the steady-state approach (when compared to the buildup analysis approach) and the calculated ventilation rates. The buildup approach has been used in past studies and demonstrated to be useful when data fit the model, meaning constant occupancy conditions exist, single-zone ventilation, constant outdoor CO_2 concentrations, and constant ventilation rate (Dols and Persily, 1995). A similar approach is described in a paper by Mudarri (1997), detailing a method to approximate steady state based on time of occupancy and assuming all conditions as described previously are in place.

Based on the analysis of CO_2 and ventilation rate data, it was concluded that the peak and predicted values of both CO_2 and ventilation rate were highly correlated. The uncertainty related to CO_2 values is estimated to be ± 280 ppm based on mean 95%CI for predicted CO_2 values; and the uncertainty related to ventilation rates is ± 1.0 l/s per person based on median 95%CI for predicted ventilation rates.

The power of the simple linear regression association between ventilation rate and either reading or math scores in the full merged database ($N = 100$) was small, and the association was not statistically significant. The data were sparse/more scattered with ventilation rates higher than the ASHRAE recommended minimum, and curve fitting indicated expanding uncertainty with higher ventilation rates. Residual and influence statistics indicated extreme values and/or greater influence of these higher ventilation rate values. The following analyses were performed using filtered data of 87 schools that had estimated ventilation rates below the recommended minimum of 7.1 l/s per person.

Based on the results using filtered data, our research suggests a linear association between substandard ventilation in a classroom and students' academic achievement; for every unit (1 l/s per person) increase in the ventilation rate, the proportion of students passing standardized math test (i.e., scoring satisfactory or above) is expected to increase by 2.9% (95%CI 0.9–4.8%), and the proportion of students passing the standardized reading test is expected to increase by 2.7% (95%CI 0.5–4.9%).

The linear relationship observed between ventilation rate and test scores may level off or change direction with ventilation rate values above 7.1 l/s per person. A point may be reached, potentially above the recommended minimum, whereby added ventilation provides no further benefit to learning. In some cases (e.g., hot/humid climates, or in heavily polluted urban outdoor ambient environments), excessive ventilation without proper filtration/conditioning of the air, may in fact be detrimental to overall outcomes. Given the limited number of observations above the recommended minimum, we are unable to test additional hypotheses: a larger sample size is needed for estimating the effect of higher classroom ventilation rates (i.e., above 7.1 l/s per person) on academic achievement. The concept of a 'no observed effect level' is significant in terms of optimizing ventilation delivery in conjunction with associated energy savings (Fisk, 2000).

It should be noted that the systems in place in the school districts primarily were operated on a fixed amount of outdoor air (fixed damper position) being provided, when the system is operating. Given that the CO_2 measurements were taken under 'occupied' periods of the day, and that the HVAC delivery to each classroom was measured with the system in constant 'fan on' operation, the variance of the ventilation provided by the system is minimized related to seasonal variations. In the studied districts, school polices in place advised teachers to keep windows closed during occupied hours throughout the school year in an attempt to conserve energy and to better control effects of the ambient environment on the indoor environment. Whereas the closed classrooms may be construed to impose conditions that may reflect an underestimation of the ventilation rate, because of the School District policy of keeping windows closed, the method employed provides a 'best' snapshot of conditions that prevail through the year and are not an underestimate. Classrooms were in session during the study, and children came and left the room in normal fashion as throughout the year. Given the challenges in working in occupied school classroom environments, the approach is consistent and best attainable.

It is also to be recognized that other parameters/stressors such as lighting and noise may factor into academic performance. However, the focus of this paper is on the association of ventilation and achievement. It is not intended to reflect all environmental parameters that may pose a detriment to learning. In addition, other factors such as temperature, relative humidity, indoor air pollutant load, etc. are not specifically detailed in this paper. It is hypothesized that these factors (such as pollutant load) may be higher or more concentrated as a function of the reduced ventilation in a classroom and thus cannot be ruled out as the underlying etiologic agents responsible for the impediment to learning.

From another point of view, SES did not seem to confound the association between ventilation rate and academic achievement in this study. Interestingly, a meta-analysis by Sirin (2005) showed a medium to strong SES and achievement relation, and the mean correlation found was 0.299, ranging from 0.25 to 0.47. According to this analysis, the most commonly used SES component is eligibility for school lunch programs. The database used for our work reveals a correlation between % free lunch participation and test scores in the range of 0.19–0.29, which is somewhat lower than the observed correlations between ventilation rate and test scores (0.28–0.31). Higher correlations (0.49–0.55) were observed between test scores and percent gifted enrollment, which could be attributed to both individual characteristics and school selectiveness, i.e., some schools attracting more gifted students. The point is that the correlation values between ventilation rate and test scores are of similar magnitude with those commonly used in the education field associating SES with achievement.

R^2-values obtained in this study are also similar to those reported in other studies with a range of individual and SES variables included. In a study by Peng and Wright (1994), race-ethnicity alone accounted for 10% of the variance in student achievement ($R^2 = 0.10$), whereas school type, home environment, and educational activities together accounted for 30% of the variance. The proportion of total variance accounted for was 33% when all variables were analyzed; thus, race-ethnicity added 3% of the accountable variance. In this study, the classroom composition measured by SES variables accounted for similar proportion of the variance, and with the other parameters fixed, ventilation rate added 3–6% of the accountable variance. However, the analysis used an outcome of the percentage of students in each classroom scoring above satisfactory; while these were the only data available for this study, student-level data on test scores would allow more detailed analyses with more power to assess any relationships between IEQ and test scores.

In summary, the results indicate that there is a linear relationship between ventilation rate and test scores for the range of schools with ventilation rates below the recommended minimum. However, the relationship between above-standard ventilation rates and academic achievement remains unclear. Therefore, we conclude that meeting the current standard for ventilation in classrooms may allow a more productive environment than would exist with lower ventilation rates. Moreover, improving ventilation and IEQ in schools is a relatively straight forward approach, whereas other means of improving students' academic performance/ achievement (e.g., socioeconomical intervention, and others) appear to be more complex.

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