Indoor Environmental Quality and Human Performance: Evidence from a Large-Scale Field Study

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Abstract

Background

Exposure to poor environmental conditions has been associated with deterioration of physical and mental health, and the reduction of cognitive performance. Environmental conditions may also influence cognitive development of children, but epidemiological evidence of such impact is scant. In OECD countries, children spend an average 930 hours per year in a classroom, second only to time spent in their bedroom. Using continuous sensing technology, we investigate the relationship between indoor environmental quality (IEQ) and cognitive performance of school-aged children, including health measures and socio-economic indicators as mediators in the analysis.

Methods and Findings

A study design is presented to reliably monitor IEQ in a school setting, at an unprecedented scale. We will monitor the IEQ of 280 classrooms for a period of 5 years, covering approximately 10,000 children. Each classroom in the sample is permanently equipped with a sensor measuring the levels of air quality (carbon dioxide and coarse particles), temperature, relative humidity, light intensity, and noise levels, all at one-minute intervals. Academic performance of school-aged children is measured by means of individual nationally standardized cognitive tests. In addition, the health status of each child in the sample is collected, together with an extensive set of socio-demographic characteristics (e.g. parental income, education, occupational status). Preliminary results from a pilot study monitoring eleven classrooms during an academic year show significant heterogeneity in indoor environmental conditions across classrooms and over time.

Conclusions

Evidence on the consequences of indoor environmental quality (IEQ) on cognitive development is limited, whereas humans spend more than 90 percent of time indoors. Focusing on schools, we find that IEQ varies significantly both during the school year and between classroom. This reinforces the question on the effects of IEQ on cognitive performance, where IEQ should be measured in a large-sample setting with a longitudinal design. The proposed study will result in a better understanding of the effects of various environmental characteristics on cognitive performance, thereby paving the way for experimental studies.

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1 Introduction

Exposure to poor environmental conditions has been associated with deterioration of physical health, mental health, and cognitive performance (Brunekreef and Holgate, 2002). However, most evidence relies on outdoor measurements and is based on samples of the adult population. There is a dearth of reliable and accurate evidence on the impact and distribution of indoor environmental conditions on human performance in general, and children's cognitive development in particular. Children are especially vulnerable to poor environmental conditions, and these conditions might well be a significant determinant of outcomes in later life.

Children in developed countries spend an average of 7,450 hours in school buildings during their primary and lower secondary education (OECD, 2016). After their home, schools are the most frequented place for children on any given weekday. Schools are also a major consumer of public funds. The U.S. alone invested USD49 billion per year in school facilities from 2011 to 2013. Yet, a recent study reports that 53 percent of U.S. public schools are in urgent need of repairs, renovation and/or modernizations (U.S. Department of Education, 2014), providing some indication that indoor conditions may be suboptimal in many schools. Understanding better the relationship between the variation in indoor environmental conditions and cognitive performance of children may thus have important implications for academia and society alike.

In this paper, we present an overview of studies that address the impact of environmental conditions on children's health and performance. We then present the design of the prospective study. We also discuss the results from a pilot study, describing the variation of environmental conditions across classrooms.

2 Literature

2.1 The effects of ambient environment on health and cognitive functioning

There is extensive evidence in the health science literature on the damaging effects of ambient environmental stressors, such as extreme temperatures or air pollution, on physical and mental health of individuals. For instance, heat waves or the presence of air pollutants, such as ozone or fine particles both have been associated with respiratory or cardiovascular diseases in humans Brunekreef and Holgate (2002); Nimon and Oswald (2013). More recently, empirical evidence shows that air pollution can also cause serious damage to human nervous systems, impairing proper cognitive functioning of people. In particular, research in the field of neuroscience suggests that exposure to air pollution is related to ischemic stroke risk, depression and mood disorders in adult populations (Calderon-Garciduenas et al., 2015; Taylor et al., 2015).

These hazards are expected to create even more severe damage among infants and young children, as the immune systems, central nervous systems, and respiratory systems are not yet fully developed at a young age (Makri et al., 2004). Quasi−experimental evidence shows that moderate levels of pollution in developed countries are associated with significant drops in birth weight, increases in school absences, and infant mortality and morbidity (Currie, 2013). Furthermore, children's behavioral responses to environmental hazards differ from adults, since children have limited decision power on how and where they spend their time. Exogenous shocks in environmental conditions might well have detrimental consequences for individual human capital accumulation and labor outcomes later in life.

Air Quality

Recent evidence suggests that the impact of air pollution on human performance goes beyond direct health channels. A recent study of 39 schools in Southern Europe finds strong associations between the level of traffic-related pollution (i.e. fine particles) and slower cognitive development among children (Dadvand et al., 2015; Sunyer et al., 2015). Similarly, Ebenstein et al. (2016) show that air pollution may also lead to immediate impairment of cognitive performance of individuals. The authors link a longitudinal dataset of 400,000 high-stake test examinations in Israel to ambient levels of pollution on the test day, documenting that a student taking an exam on a day with high pollution (measured by levels of fine particles) scores, on average, 2.3 percent lower.

Indoor air quality (AIQ) is not purely a by-product of outdoor air pollution, or purely generated by outdoor sources alone. Rather, it is the result of a complex process affected by building conditions and occupant-related factors (Madureira et al., 2016). The most commonly used indicator of IAQ is the concentration of CO2, a colorless, odorless gas that is metabolically produced by humans. CO2 is also used as a metric to evaluate the performance of ventilation systems in buildings. The inhalation of high levels of CO2 has been associated with respiratory and cardiovascular problems in humans (Seppänen and Fisk, 2004; Stankovic et al., 2016; Sundell et al., 2011).The health science literature documents multiple physiological symptoms related to poor ventilation in rooms, such as fatigue, headaches, and prevalence of asthma episodes (Annesi-Maesano et al., 2013).These health issues, ultimately, have also been associated with an increase in absence from work and school for adults and children, respectively (Mendell et al., 2013; Shendell et al., 2004).

Studies in the field of epidemiology and neuroscience show significant impairments in cognitive performance associated with poorly ventilated rooms (i.e. high levels of CO2). Experimental evidence from functional magnetic resonance imaging (fMRI) in the field of neuroscience documents reduction in brain activity following inhalation of 5% (50,000 ppm) CO2 (Xu et al., 2011).

Recent lab evidence suggests significant effects of moderate CO2 concentrations on the cognitive performance of individuals beyond the aforementioned health channels. These studies typically evaluate the performance of healthy adults on different cognitive tasks in rooms where CO2 levels have been manipulated. Zhang et al. (2017) show significant reductions in the speed of addition, increased response time in a redirection task, and an increase in the number of errors made by adults when undertaking those tasks in rooms with a CO2 level of 3,000 ppm (relative to 500 ppm). Satish et al. (2012) find that, relative to a baseline of 600 ppm of CO2 (close to outdoor levels), healthy adults exposed to 2,500 ppm of CO2 for 2.5 hours scored 44 to 94 percent lower along different cognitive dimensions, such as crisis response, or information usage. Using a similar study design, Allen et al. (2016) document a 50 percent reduction in cognitive performance after being exposed for 6 hours to CO2 levels of 1,400 ppm (relative to 550 ppm).

Temperature

The literature also highlights the role of temperature in affecting human health and performance. In particular, strong links have been found between extreme temperatures and morbidity and mortality in developed and developing countries (Patz et al., 2005). In addition, there is increasing evidence from quasi-experimental field studies concerning the health and cognitive implications of sharp variations in day-to-day temperatures (Hancock et al., 2007). Park (2017) studies the effects of outdoor temperature during exam days on student performance, using 4.6 million high school exit tests in New York. The author finds that students taking an exam on a day with temperatures higher than 32 ?C score up to 15 percent lower. Cho (2017) explores the effect of temperature on student learning. In a cohort study including 1,729 high schools in Korea (some 1.6 million students during 5 years) the author explores the changes in student test scores within schools associated with heat waves during the academic year. The estimates show a drop in math and English tests of 0.0042 and 0.0064 standard deviations for days with a maximum daily temperature above 34 °C, relative to days with a maximum daily temperature between 28 °C and 30 °C.

Lab experiments equally show the detrimental effects of passive heat on stress and human cognitive function. These studies experimentally manipulate the exposure to high temperatures (50 °C, 50% r.h.) over short periods (45 mins) and look at changes in performance on cognitive tasks. The results indicate that individuals under heat stress perform worse in complex tasks such as working memory or executive function (Gaoua et al., 2011; Taylor et al., 2015). Studies in the area of neuroscience suggest that these drops might be a consequence of alterations in blood flow and brain activity associated with heat stress (Taylor et al., 2015). The effects of extreme temperatures on performance and health are likely to be even more damaging when coinciding with other environmental factors, such as high relative humidity (Barreca, 2012) or air pollutants such as ozone (Breitner et al., 2014).

2.2 Existing Studies on Indoor Environmental Quality in Schools

Schools are commonly regarded to have poor indoor air quality, resulting from a combination of high occupancy and poorly ventilated spaces. Numerous studies show that CO2 concentrations in schools frequently go beyond the levels that facilitate proper cognitive functioning of occupants. These thresholds have been defined by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) and are typically used as cut-offs in academic research, including the studies in epidemiology or neuroscience discussed in the previous section (Fisk, 2017). However, the evidence on the implications of deficient environmental conditions in classrooms for learning outcomes is still scant, and the magnitude and distribution of the impact of indoor environmental quality (IEQ) on children?s school performance remains an open question.

The most recent review of the literature identified 27 studies exploring the link between ventilation rates and CO2 on children?s academic achievement or health (Fisk, 2017). The current analyses tend to focus on one unique measure of environmental conditions (e.g. average temperature in a classroom or average CO2 over the measurement period) as main explanatory variable. Most studies are therefore not able to differentiate between the effects of indoor climate on learning and testing performance. This differentiation is critical for the interpretation of results and policy implications of any study.

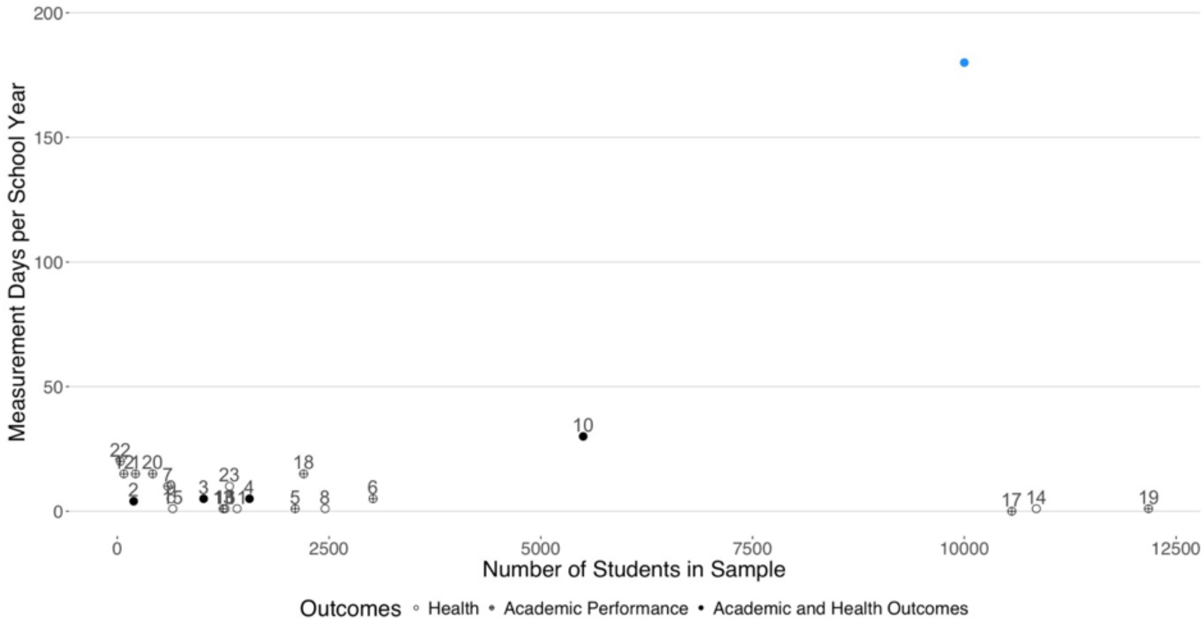
The current evidence on indoor environmental conditions in schools and student performance mostly relies on between-subject comparisons and do not contain information on health outcomes at the individual level. The limited number of students in the typical sample, the use of classroom-aggregated variables and the lack of background information about students hinder examination of channels or heterogeneous effects of climate on student achievement. The lack of availability of testing measures for younger children makes all of the available studies, with one exception (Gaihre et al., 2014), rely on samples of pupils at the end of their primary/elementary education (age 10-12). The systematic exclusion of younger children from studies might well have important consequences for the estimated effects of poor environmental conditions. Children?s developing bodies experience significant changes in respiratory, immune and neurological systems. In addition, learning goals and challenges differ between the age of 4-5 and the age of 10-12, impeding the direct extrapolation of findings from older children to younger children.

Examining the relationship between air quality or temperature and cognitive performance or health is a challenging task, as there are many confounding factors. The presence of unobserved school or classroom characteristics that are potentially correlated with indoor conditions is likely to pollute any estimate on the effect of indoor air quality on health or academic outcomes. Thus, it is necessary to measure indoor environmental conditions for a large number of classrooms over multiple years to let participants be exposed to different indoor environmental conditions while undertaking comparable tasks. The current literature often highlights the lack of statistical power in tests due to the low number of observations in their analysis. This is the result of a small number of individuals in the sample (typically less than 2,500 individuals) and the collection of one testing outcome per child and subject (e.g. Madureira et al., 2016). The low number of observations leads to wide confidence intervals, often resulting in a failure to reject the null hypothesis of deficient climate conditions affecting academic achievement.

Finally, the current literature lacks data on individual health profiles and socio-demographic characteristics of children. Most studies have access to absence days or gender ratios at the grade or classroom level only (e.g. Mendell et al., 2015). The lack of individual characteristics in the analysis hinders the examination of potential heterogeneous effects of climate conditions on children?s academic achievements. This is critical for the policy recommendations of a study, since it allows for the identification of specific target groups (e.g. asthmatic kids) and ultimately advice on more effective interventions or investments (e.g. ventilation system versus heating system).

For a graphic overview of the existing literature, and to provide a comparison with the research setup of our study, we collected information on the number of measurement days and number of individuals in all current studies investigating the effects of indoor school environment on health and/or academic performance (figure 1). Operational limitations typically make researchers face a tradeoff between measurement time and sample size (i.e. the number of classrooms monitored). Over 90 percent of the studies rely on short term measurements (less than 10 days) and not a single study performs analyses on measurement periods longer than 30 days. Stability in occupancy rates and usage of classrooms within the academic year tend to reduce variance in environmental conditions in classrooms. However, the changes in ambient conditions (outdoor climate or pollution) and in the built environment (i.e. building modification or depreciation) create meaningful deviations in environmental conditions over time. Each dot in figure 1 represents one study, distinguishing between studies that focus on health, academic performance, or both. For comparison, our own study is depicted in the larger blue dot in the upper right corner. We note that, since the graph depicts observations days per school year, whereas our study will cover four consecutive school years, it understates the difference between our study and the existing literature.

Figure 1: Current studies on IEQ and cognitive performance in children.



Note: The references of the studies included the graphs are [1] (Bakó-Biró et al., 2012), [2] (Dorizas et al., 2015), [3] (Ferreira and Cardoso, 2014), [4] (Gaihre et al., 2014), [5] (Haverinen-Shaughnessy et al., 2011),[6] Haverinen-Shaughnessy et al. (2015), [7] (Hutter et al., 2013), [8] (Kim et al., 2011), [9] (Kolarik et al., 2016), [10] (Mendell et al., 2013, 2015), [11] (Mi et al., 2006), [12] (Petersen et al., 2016), [13] (Shaughnessy et al., 2006), [14] (Shendell et al., 2004), [15] (Simoni et al., 2010), [16] , [17] (Stafford, 2015), [18] (Toftum et al., 2015), [19] (Toftum et al., 2015), [20] (Twardella et al., 2012), [21] (Wang et al., 2015), [22] (Wargocki and Wyon, 2007), [23] (**?**). For the studies whom the number of students in the sample are reported (Shaughnessy et al., 2006; Shendell et al., 2004) we consider the average class size to be 25 pupils. The blue dot represents the study design presented in this paper.

3 Methods

3.1 The elementary education system in the Netherlands

In a typical Dutch elementary school, children attend class from 8:30am until 3:15pm. Children have the option to consume their lunch at home during the one-hour lunch break or eat their self-brought lunch at school. The amount of time that children spend in the classroom is second only to the time they spend in their bedroom, and it generally increases as children progress in elementary school.

The elementary education in the Netherlands consists of 8 years, from the age of 4 to the age of 12, being compulsory from the age of 5 only. The education system is ruled under the principle of ”freedom of education”, where elementary schools are granted a high degree of autonomy, giving the right to any natural or legal person to set up a school and to organize its teaching program. At the same time, the central government sets learning objectives and quality standards that apply to all schools, monitoring school quality and compliance with central rules and regulations. Nearly all schools participate in the well-developed nationally standardized assessment system, the Leerling Volg Systeem (LVS), a longitudinal student tracking system comprised of multiple tests per grade, covering the main knowledge areas and developed by the Central Institute for Test Development (Centraal Instituut voor Toetsontwikkeling, Cito). The tests take place throughout the academic year, with clear testing peaks in January, February and June. By the end of the primary education, in the 8th grade, Cito's Entreetoets supports elementary schools in their recommendations regarding the level of high school education most suitable for each student.

3.2 Study sample and study design

Our study is designed to monitor the indoor environmental conditions and learning outcomes in approximately 280 classrooms, covering about 10,000 pupils. The levels of CO2, particles, temperature, relative humidity, background noise and light intensity of each classroom, as well as student performance in the sample will be continuously monitored for four consecutive academic years, starting September 2018.

The 23 schools involved represent a random sample of the schools belonging to an educational board with 47 schools under management, in the South of the Netherlands. All schools are situated in an area that is economically slightly deprived, with a rather large proportion of inhabitants that have a low socioeconomic status. Relatively few children achieve an adequate starting qualification for the labor market, and a large number of children leave high school without a certificate (Frontczak et al., 2012). All schools in the sample teach the full range of grades (i.e. grades 1-8) in their education program. The average amount of classes per school is 11. The sample is quite heterogeneous with regards to building characteristics. The average school building in the sample was built in 1987, and the date of construction ranges from 1932 to 2016. All classrooms have internet connection and multimedia boards for teaching practices. The buildings are also heterogeneous in terms of ventilation system. Approximately half of the buildings have a ventilation system (52 percent), and 23 percent of the school buildings have a ventilation system that was installed in the last 5 years.

3.3 Monitoring Environmental Conditions in Classrooms

Environmental conditions in each classroom will be monitored using the Aclima measurement system (Aclima Inc., San Francisco, CA). Spatially and temporally resolved indoor data is collected using a sensor network consisting of individual wall-mounted stationary nodes, all equipped with a number of individual sensor modules. For this study, the nodes will measure CO2 (ppm), coarse particles (counts/L), temperature (C), relative humidity, light intensity (lux), and sound (dBA). The node captures and transmits all data to a cloud-based server, where the data is processed, analysed, and stored. See Table 1 for the sensor performance characteristics. The frequency of raw data collection ranges from 1 to 30 seconds. However, we implement a smoothing protocol that aggregates all measures at the 1-minute level, using moving averages. With the exception of coarse particle counts, that will be aggregated at 15-minute intervals.

Table 1: Sensor Characteristics

	Sensing method	Accuracy	Resolution	Sample frequency
Carbon Dioxide (CO_2)	Non-dispersive infrared	50 ppm + 3%	10 ppm	17 sec
Coarse Particles (PM)	Optical, scattered light	250 count/L + 20%	250 count/L	30 sec
Relative Humidity (rh)	Complementary metal oxide semiconductor	0,04	0.3%	5 sec
Light (lux)	Photodiode	3 lux		1 sec
Temperature (C)	Solid state integrated circuit	1 C	0.2 C	1 sec
Sound (dB)	Back electret	5 dBA	3 dBA	1 sec

An important channel for indoor environmental quality on place and occupant performance is the perceived quality of the environment. To explore the level of comfort at different schools and classrooms, we assess (1) teachers and (2) students by using annual questionnaires. For teachers, we use the Occupant Indoor Environmental Quality Survey developed by the Center for the Built Environment at the University of California, Berkeley (Madureira et al., 2016). The questionnaire includes questions about thermal comfort, perceived air quality, and noise. For students, we ask a cohort of 1,000 pupils, starting at age 10 (all pupils in group 6 in the sample), to report annually on their perceptions of odor intensity and acceptability by using a series of visual scales, previously validated in the literature (see Madureira et al., 2016).

In addition, we also retrieve daily information ambient temperature from the Global Historical Climatology Network (GHCN) of the National Oceanic and Atmospheric Administration (NOAA) and outdoor levels or air pollution from the Dutch National Air Quality Monitoring Network (LML).

3.4 Student performance

We exploit an existing infrastructure that tracks student performance, based on standardized tests (the LVS tracking system), regular evaluations by the teachers, the Cito final test, student and teacher attendance, student socio-demographics and their attitudes toward the school (see Table 2 for an overview of the data). This dataset is part of OnderwijsMonitor Limburg (OML) within the Educational Agenda Limburg that monitors educational development and teacher quality (See Borghans et al. (2015b,a) and Willeboordse et al. (2016a) for previous studies using this data).

In our sample of schools, the dataset contains a total of approximately 36,000 standardized tests per year (6 tests per child). Each child takes an average of 2 tests per year per subject. The tests comprise a wide variation of educational areas, such as reading, math, language and foreign language tasks (English). The dataset includes individual identifiers for each child in the dataset, allowing to follow children over the entire study period, and to explore changes in the test scores of a child. The panel structure of the dataset also allows for the exploitation of variation in environmental conditions, linking it to test scores at the individual level. In addition, the final dataset will include accurate information of the time and place of each of the tests in the sample, enabling differentiation between contemporaneous effects (i.e. at the time of testing) and permanent effects (learning).

Table 2: Student performance assessments

National tests	**School tests**	**Study tests**
Cito LVS tracking tests groups 3−8	Grades (four times/year)	Self−efficacy pupils
Cito final test group 7	School advice on secondary education	Strengths and difficulties questionnaire
	Actual ongoing education	

3.5 Individual Characteristics

Individual Health Outcomes

We gather data on health outcomes for children in the sample from multiple sources. Annual absence days of children will be collected by OML and the registration records by the educational board. For students enrolled in five sample schools, we will complement information on the student profile with general health measures of the child, combining multiple sources. All health outcome measures origin from an already existing longitudinal study on health and lifestyle of pupils. See Willeboordse et al. (2016b) for a detailed description of all general health measures. Information on general health outcomes will be derived from an online parental questionnaire covering: disease status since birth, hospital admissions (number and duration), healthcare visits (number), and medication use in the previous 12 months (See Appendix A, B and C for the English translation of the exact questions in the questionnaire.). Anthropometric measurements, including height, weight, hip, and weight circumference will be objectively and separately collected for all children. Information on birth weight and additional information on disease status will be collected via the Regional Public Health Services (GGD).

Household socio-economic characteristics

In addition to academic and health outcomes, we gather a complete profile of household socio-economic characteristics of the pupil. These factors have been shown to be important

Table 3: Health Outcomes

Health Measure	Source
Birthweight (subsample of 5 schools)	Regional public health services (GGD)
Disease status, hospital admissions, medicine use, healthcare visits (subsample of 5 schools)	Parental questionnaire and GGD
Anthropometrics (subsample of 5 schools)	Objective measurement in children
Absence days	Onderwijs Monitor Limburg (OML)
Frequency of pupil absence and sick leave	Educational board

mediators on the link between pupil health and academic achievement (Currie, 2009). This information is available for every pupil in the dataset and contains information on parental income, occupational status, education, and parental health.

3.6 Medical ethical approval

No personal data will be collected for this study, therefore Medical Ethical Approval is not needed. Data on student performance and health stems from an already existing data infrastructure, respectively OML and the study entitled 'The Healthy primary School of the Future' (HPSF). Medical Ethical Approval for HPSF was waived by the Medical Ethical Committee of Zuyderland, Heerlen (METC 14-N-142). Data collection from GGD-ZL is executed by researchers of HPSF, this procedure has been fully approved by the Medical Ethical Committee of Zuyderland. The questionnaires on level of comfort will be filled in anonymously by students and teachers. All data records will be assured anonymized and confidentially according to the Dutch data protection law.

4 Pilot Study

In this section, we present the results of a pilot study, carried out in multiple classrooms in two schools, for a complete academic year (2016-2017). The aim of the pilot study is to test the spatial and time series variation of indoor environmental conditions in schools. We first describe the characteristics of the schools selected for the pilot, and we then present a pilot test on the number of sensors per classroom needed to accurately measure indoor environment accurately. In the second pilot test, the cross-classroom variation in indoor environmental conditions is tested over the course of an academic year.

Two schools with heterogenous physical characteristics were selected for the pilot, with the aim to maximize differences in environmental conditions. Pilot School 1 represents a relatively new school, with a modern ventilation system in a rural area. Pilot School 2 is a school built over 20 years ago, with a mechanical ventilation system that initially did not cover the classrooms, but that was redesigned to do so during our pilot study. This school is located in an urban area. The location and building characteristics of the schools are thus expected to generate differences in indoor environmental parameters. In the pilot schools none of the teachers have control over the temperature in their classrooms.

Table 4: Student performance assessments

	Pilot School 1	**Pilot School 2**
Construction Year	2010	1992
Ventilation in classrooms	Yes	No
Area Characteristics	Rural	Urban
Control Over Temperature	No	No

4.1 Pilot Test 1: Differences in environmental conditions within and across classrooms

The first phase of the pilot study is aimed at exploring the differences in environmental conditions within classrooms. For this purpose, we deployed 3 sensors in four classrooms (12 sensors in total) monitored for a period of 5 months (August 2016-January 2017). The sensors were deployed at the same height (1.50 meters) and in three separate locations covering the perimeter of the classrooms. [1] The height was chosen following current guidelines for air quality monitoring at schools (WHO, 2011). In one of the classrooms at Pilot School 2, we further investigated the differences in measurements at different heights (1.50 versus 2.00 meters) and the results show high correlations between the measurements of the sensor mounted at 2 meters versus the other two sensors installed in the same classroom.

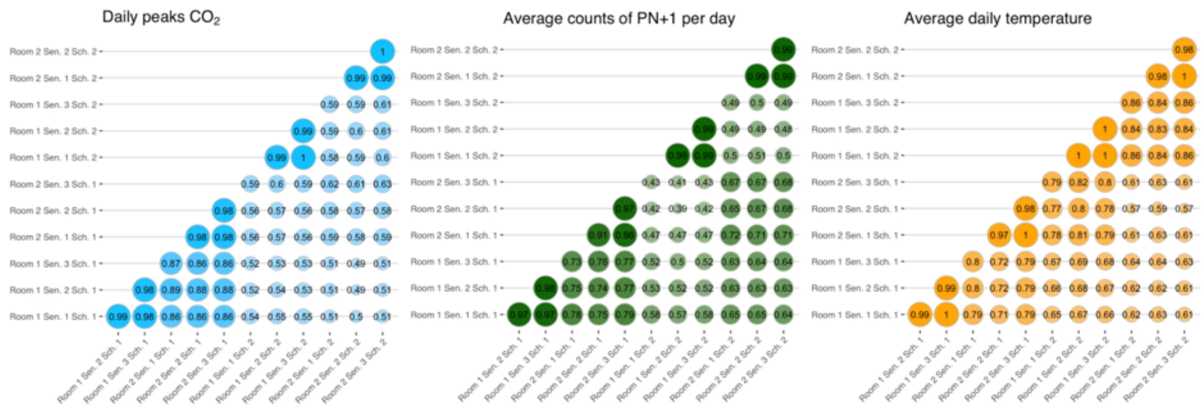
Figure 2 presents the Pearson correlation coefficients between the sensors and respectively CO2, coarse particles and temperature for the first phase of the pilot study. The results indicate that the correlations for CO2, coarse particles and temperature between the three sensors within one classroom are on all occasions very high (over 0.98). Correlations of indoor environmental metrics are always higher between the sensors within a classroom than with sensor measurements in different classrooms in a school. Especially the variation in indoor temperature and CO2 levels is highly heterogenous between classrooms, as can be observed from figure 2. The correlation between sensors in different classrooms in the same schools is higher in Pilot School 1, the newly constructed school with a mechanical ventilation system, suggesting a higher degree of homogeneity in the school.

These graphs provide important information on the heterogeneity of indoor environmental conditions within a room, and the heterogeneity across rooms. From a measurement perspective

[1] Photos of sampling locations in the classrooms of the pilot schools are shown in Appendix.

the results suggest that there is unique information to obtain from each node, thus reinforcing the need to measure each room individually. However, deploying more than one sensor per room seems to be redundant.

Figure 2: Correlation in CO_2, coarse particles and temperature within and across classrooms.



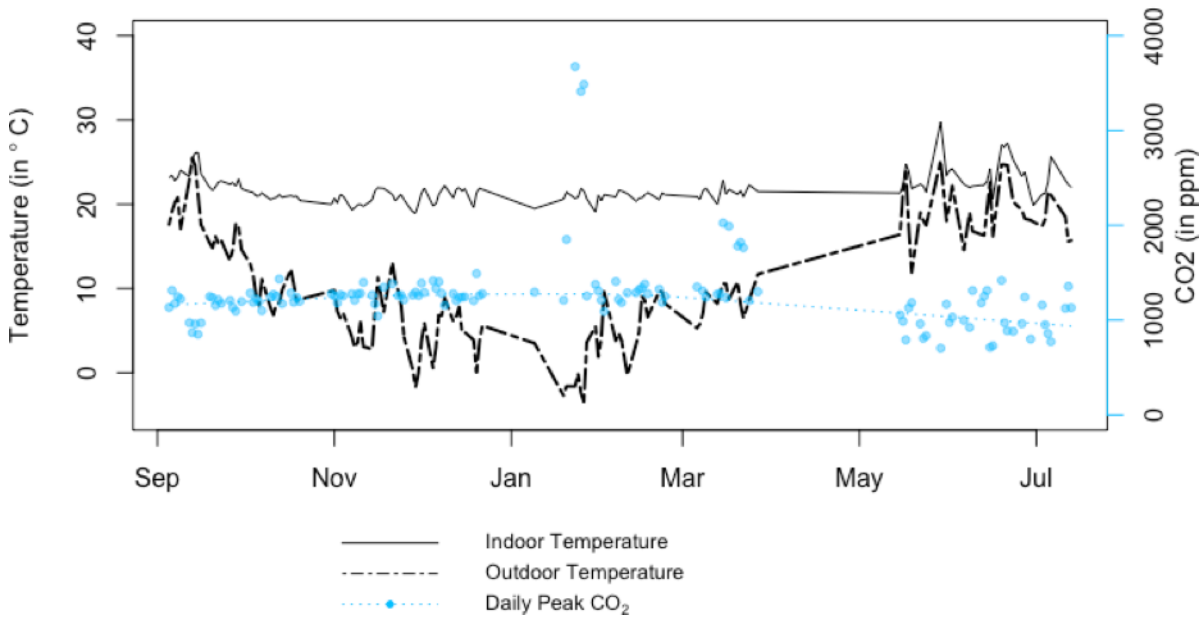
Note: The figure presents the Pearson correlation matrixes of the daily average of temperature, coarse particles (PN) and peaks of CO2, measured at different locations within 4 classrooms: 2 classrooms in a relatively new school ("School 1") and 2 classrooms in an older one ("School 2").

4.2 Pilot Test 2: Time-series variation of sensors over the academic year

The second part of the pilot study aims to test the variation in indoor environmental conditions in the selected sample of classrooms over the period of one academic year. For this study, 12 sensors were placed in 10 classrooms and one computer room, divided over the two pilot schools described above. Figure 3 shows the variation in indoor temperature and CO2 levels over the course of a year for a classroom in Pilot School 1, along with the ambient temperature in the area of the school. The outdoor temperatures were gathered from the U.S. National Oceanic and Atmospheric Administration (NOAA) and correspond to the average daily temperatures measured at the nearby Maastricht Airport weather station. The average daily temperature in the classroom during learning hours ranges from 19 C to 30 C, with an average of 22 C. The daily peaks of CO2 increase when the ambient temperature drops, fluctuating around 1,300 ppm in the cold season and around 1,000 ppm in the warm season.

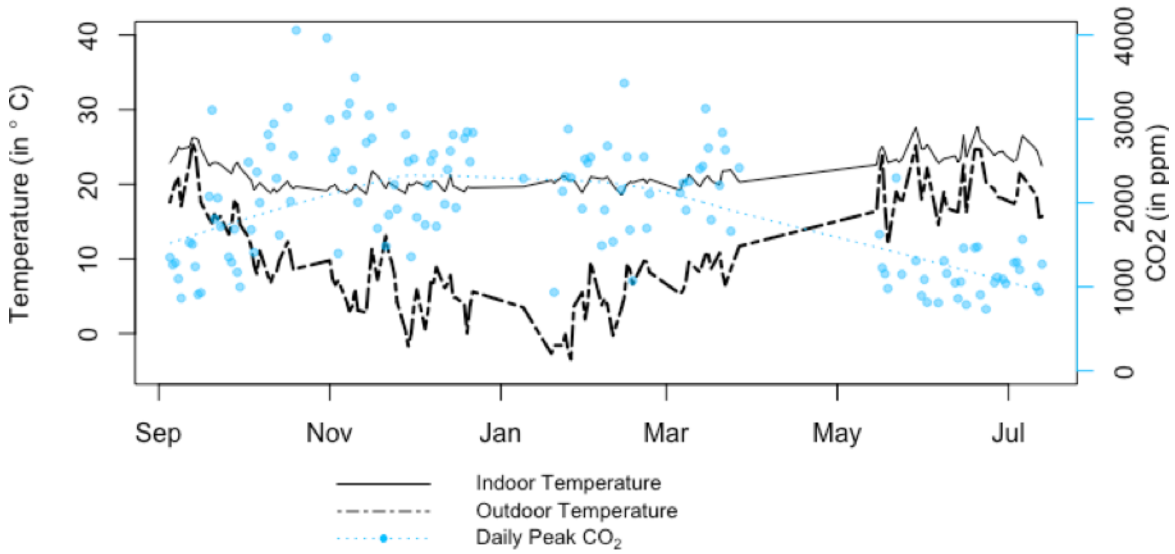
Compared to Pilot School 1, the variation in indoor temperature and CO2 levels over the course of a year in Pilot School 2 is quite high, as figure 4 illustrates. The figure highlights that the average daily temperature in the classroom during learning hours ranges from 19 C to 28 C, with an average of 21 C. The daily peaks of CO2 again increase when the ambient temperature

Figure 3: Temperature and CO_2 levels over the 2015-2016 academic year in classroom 1 of School 1 (with mechanical ventilation).



drops, fluctuating around 2,000 ppm in the cold season and around 1,000 ppm in the warm season.

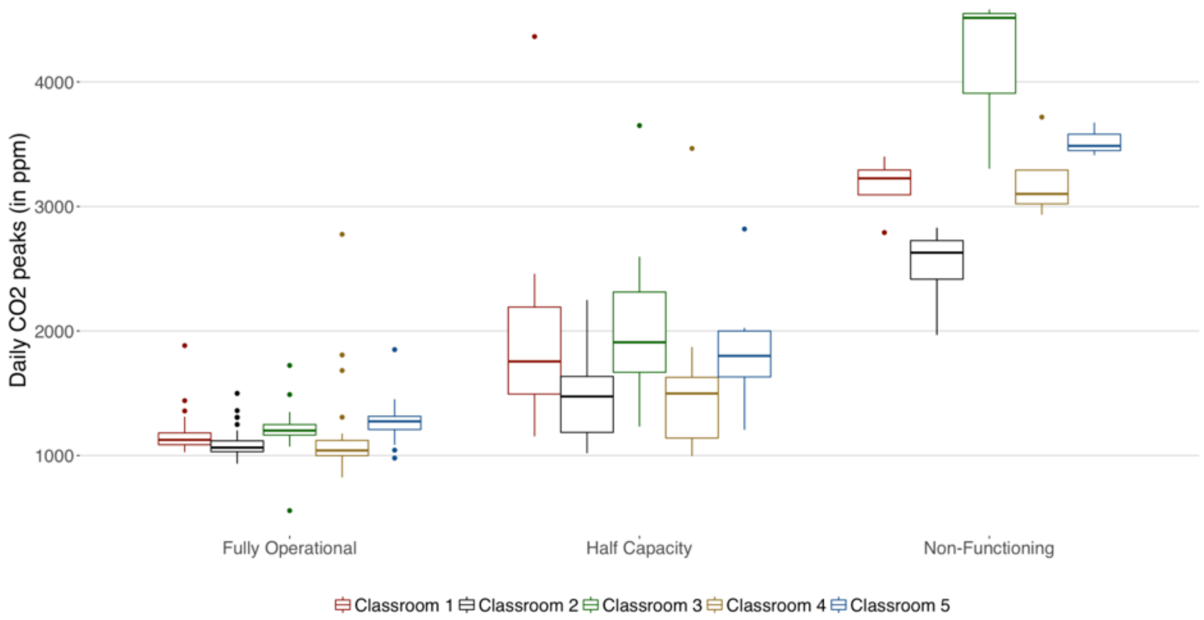
Figure 4: Temperature and CO_2 levels over the 2015-2016 academic year in classroom 1 of School 2 (without mechanical ventilation).



There are significant differences in the levels of CO2 in the cold season, when teachers close the windows to keep the temperature in the classroom within acceptable levels for teaching. In the school with a ventilation system (figure 3) the daily peaks of CO2 are on average 700 ppm lower than in the school without a ventilation system (figure 4). The difference becomes less pronounced during the warm season, when teachers in the naturally ventilated school frequently open the windows. The influence of ambient temperature on indoor temperature is higher in the summer period for both schools, when the lack of air conditioning even exposes pupils to temperatures surpassing the (already high) outdoor temperature.

During the academic year, it became apparent that indoor environmental quality is strongly associated with the status of building conditions and the status of the mechanical ventilation system. This is illustrated by the effects of a breakdown and modification of a ventilation system (figures 5 and 6). In January 2017, the ventilation system in Pilot School 1 had to be switched off for a week due to problems with the engines. In March 2017, half of the engines in the ventilation system were not working, so the ventilation system worked at half capacity for seven school days. As a result, the levels of CO2 increased by 50 to 70 percent, and tripled during the days where the ventilation system was not functioning at all.

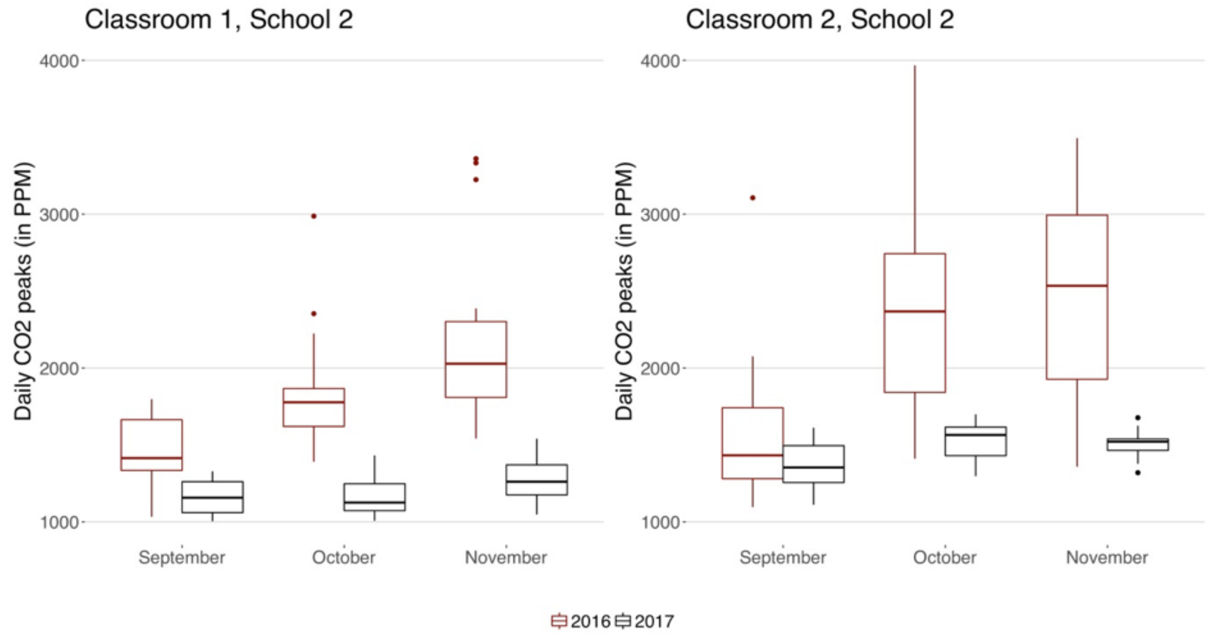
Figure 5: Distribution of daily CO2 peaks over the 2016 2017 academic year in Pilot School 1 for three scenarios in the ventilation system conditions.



Note: The ventilation breakdown period took place in January 2017 and the ?Half-Operational? period took place in March 2017. The fully operational block is computed using the CO2 peaks in January, February, March and April excluding the days where the ventilation system was not working properly.

We also observed a strong impact of modification of the ventilation system on classroom CO2 levels. In January 2017, the ventilation system in Pilot School 2 was modified to increase its coverage of the classrooms. The distribution of CO2 levels after the modification was significantly lower than the distribution before the change, reducing the exposure of children to high levels of CO2 (figure 6). We did not observe any systematic change in the distribution of the other IEQ characteristics collected by the sensor (see Appendix C for distribution of coarse particles and temperature before and after the modification).

Figure 6: Distribution of daily CO2 peaks in Classroom 1 and Classroom 2 of Pilot School 2 before and after modification in ventilation system.



5 Conclusions

There is extensive evidence that exposure to poor environmental conditions is associated with deteriorations in physical health, mental health, and cognitive performance. However, most of the studies rely on outdoor measurements of environmental conditions and on samples of the adult population. Scientific evidence on the relationship between indoor environmental conditions and cognitive performance is scant, particularly for children, which arguably have most to lose from exposure to detrimental condition. From a methodological perspective, the literature is constrained by small samples, relying on between-subject comparisons rather than within-subject comparisons, making it hard to establish causality. This paper describes the design of a longitudinal study in which the environmental conditions of more than 10,000 children will be monitored during four academic years and will be related to individual measures of academic performance and health. The study has a robust design to measure indoor environmental quality in a school setting, using state-of-the-art sensor technology to objectively measure the environmental conditions at high frequency.

From the first pilot study, we conclude that the exact placement of sensors in a classroom does not affect the ability of the sensor to accurately measure indoor environmental conditions. The additional information content from installing multiple sensors, relative to a singular sensor, to accurately measure indoor environmental quality within a classroom is low. Placement of one sensor at briefing height provides robust measurements of the indoor environment in a classroom setting. At the same time, indoor climate conditions differ considerably across classrooms, indicating that sensors need to be installed in each individual classroom in a school.

The second pilot study shows that the variation of various indoor environmental quality characteristics over the course of one academic schoolyear is high. Due to the high variation of IEQ during the schoolyear, a longitudinal design of at least one academic year is necessary to robustly measure the impact of indoor environmental quality on health and academic outcomes.

The proposed study will clarify to which degree different environmental characteristics influence cognitive performance, taking into account the health of pupils. The correct placement of sensors, the longitudinal design, and the large number of pupils included in the study will add valuable knowledge to the current literature. If it turns out that indoor environmental quality is indeed salient for the performance of young children, the next stage will be to design field experiments. By optimizing air, light and sound in classrooms, cognitive performance can possibly be improved. As changes in indoor environment are often low-cost and easily implementable, the direct societal and scientific importance of the findings in this study may be substantial. Indirectly, this study may affect how school buildings are built, managed, and maintained, both in the Netherlands and across the globe.

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Appendix A: Respiratory diseases

Table 5: Disease prevalence of children

	Child suffered this before primary school	**Child suffered this during primary school**	**My child currently has this disease**	**It has been diagnosed by a doctor**
Asthma or chronic bronchitis	Yes/No	Yes/No	Yes/No	Yes/No
Hay fever or allergy to dust / animals / medicines	Yes/No	Yes/No	Yes/No	Yes/No
Throat, nose or ear infections	Yes/No	Yes/No	Yes/No	Yes/No
Pneumonia	Yes/No	Yes/No	Yes/No	Yes/No
Allergy for certain foods (eg. gluten, lactose)	Yes/No	Yes/No	Yes/No	Yes/No
Eczema or other skin conditions	Yes/No	Yes/No	Yes/No	Yes/No

Appendix B: Medicine Use

Did your child regularly used medicines for the past 12 months?

- Yes
- No
- I'd rather not fill in

If yes: What medication does your child use and what? If necessary, include the package. Homeopathic remedies do not need to be filled in here. Example: Ventolin, 2 times a month, 100 mg, 2 months used, used for asthma.

Table 6: Medicine usage of children

What medicine did your child use?	**How often per day / month?**	**Dose**	**How many months did your child use this medicine during the previous year?**	**What did your child use these medicines for?**
Medicine 1:				
Medicine 2:				
Medicine 3:				

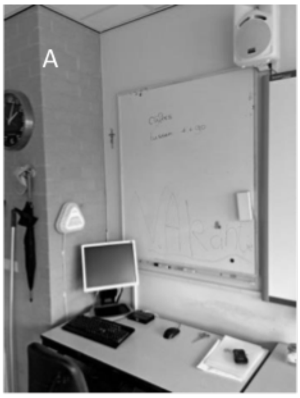
Appendix C: Current treatments

Has your child been treated by organizations and/or doctors mentioned below during the last 12 months? You can check multiple options. If you have not been in contact with one of the organizations, you can check 'no'.

Table 7: Current treatments

Organizations / Assistants	Number of contacts in the last 12 months	What was/were the reason(s) for treatment?
General Practitioner	... times	
Medical specialist: Pediatrician	... times	
Medical specialist: Ophthalmologist	... times	
Medical specialist: E.N.T. Specialist	... times	
Medical specialist: Orthopedist	... times	
Other medical specialist in the hospital.	... times	
Please specify:		
Speech therapist	... times	
Youth Care Office	... times	
Youth care or child protection	... times	
No		
Youth psychologist or psychiatrist	... times	
Other, please specify:	... times	
... ...		
... ...		
... ...		
No, I would rather not fill in		

Appendix D: Pictures Deployment Pilot Study



Sensor 1 Pilot School 1

Sensor 2 and 3 Pilot School 1

Sensor 1 Pilot School 2

Sensor 2 and 3 Pilot School 2

Appendix E: Modification Ventilation System Pilot School 2

Figure 7: Average daily counts of Coarse Particles (count/L) in Classroom 1 and Classroom 2 at Pilot School 2 over the fall of the academic year 2016-2017 before and after the ventilation system is modified (January 2017).

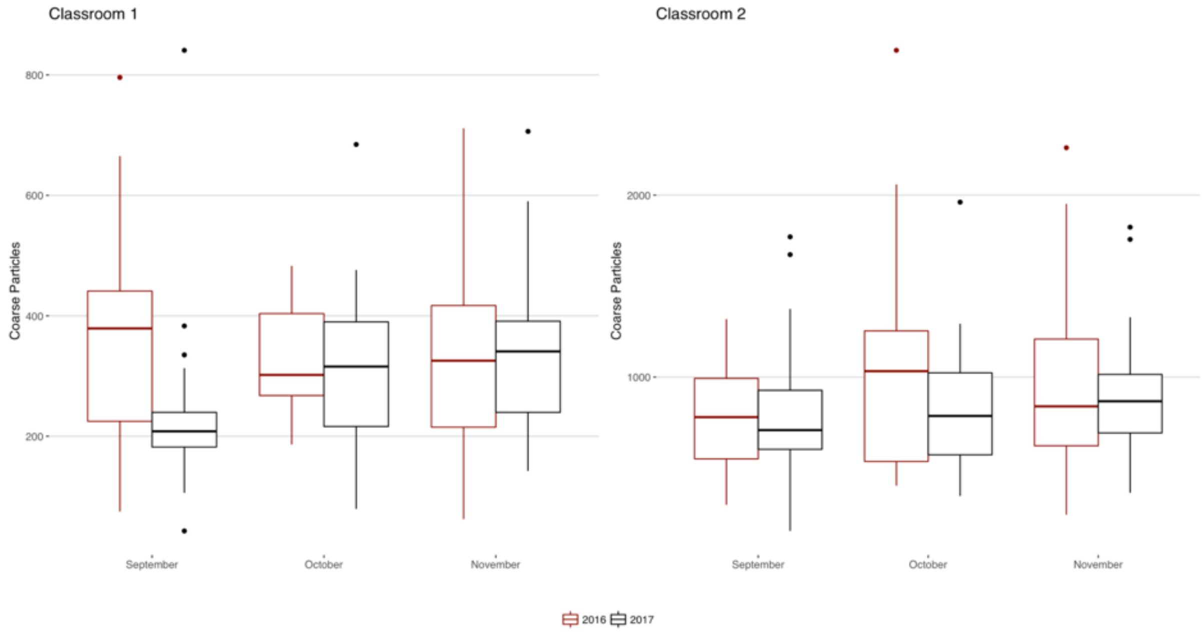


Figure 8: Average daily Temperature (in C) in Classroom 1 and Classroom 2 at Pilot School 2 over the fall of the academic year 2016-2017 before and after the ventilation system is modified (January 2017).