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INVESTIGATING THE EFFECTS OF   
INDOOR AND OUTDOOR ENVIRONMENTAL QUALITY ON   
THE ACADEMIC ACHIEVEMENT IN SCHOOL-AGE STUDENTS

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INVESTIGATING THE EFFECTS OF   
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THE ACADEMIC ACHIEVEMENT IN SCHOOL-AGE STUDENTS

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**ABSTRACT**

**CHAPTER I**

## INTRODUCTION AND LITERATURE REVIEW

Academic achievement as an important predictor for current and future success and well-being.

Academic achievement, typically measured by test scores and grades, is an important predictor of children’s current and future success and well-being. Previous studies on children found a strong correlation between current health status and current [1,2](https://sciwheel.com/work/citation?ids=11413479,11413483&pre=&pre=&suf=&suf=&sa=0,0) and future academic performance. [3](https://sciwheel.com/work/citation?ids=11413488&pre=&suf=&sa=0) Additionally, high academic performance at school or in college is an indicator for higher educational attainment, [4](https://sciwheel.com/work/citation?ids=11413502&pre=&suf=&sa=0) higher salaries, [5](https://sciwheel.com/work/citation?ids=11413495&pre=&suf=&sa=0),[6](https://sciwheel.com/work/citation?ids=11413498&pre=&suf=&sa=0) higher reported life satisfaction and happiness, [7](https://sciwheel.com/work/citation?ids=11413517&pre=&suf=&sa=0) and better health status as adults. [8,9](https://sciwheel.com/work/citation?ids=11413493,3542885&pre=&pre=&suf=&suf=&sa=0,0)

Indoor environmental quality and academic achievement

School-age children spend most daytime hours at school, just following time spent at their home. As compared to children’s homes, schools may have worse indoor environmental quality (IEQ), including indoor air quality, thermal comfort, visual quality, and acoustics.[10](https://sciwheel.com/work/citation?ids=8965239&pre=&suf=&sa=0) Poor indoor air quality (measured as the presence of allergens, mold, and bioaerosols, chemical and volatile organic compounds, and particulate matter ≤2.5 microns concentration (PM2.5) were associated with an increase in respiratory and allergy symptoms and with school absences.[11](https://sciwheel.com/work/citation?ids=8964323&pre=&suf=&sa=0) Inadequate classroom ventilation and high concentrations of carbon dioxide (CO2) were inversely associated with student performance, student health, and student attendance. Student performance was measured by either standardized academic achievement (AA) tests or special cognitive tests.[12](https://sciwheel.com/work/citation?ids=8963651&pre=&suf=&sa=0) Other environmental factors, such as thermal comfort, acoustics, and poor lighting, were associated with low motivation, but there is not enough evidence for their association with student mental health and academic achievement.[11](https://sciwheel.com/work/citation?ids=8964323&pre=&suf=&sa=0)

Among current literature on IEQ and AA, most of the previous studies used a cross-sectional design. [13](https://sciwheel.com/work/citation?ids=10082348&pre=&suf=&sa=0) In addition, confounding variables, such as socioeconomic status, and residential exposure were not simultaneously measured and adjusted for. There is evidence that these factors have greater effects on student academic performance; [11](https://sciwheel.com/work/citation?ids=8964323&pre=&suf=&sa=0) thus, accounting for these variables when assessing the effect of IEQ is imperative. Due to the inherent challenges of a large number of variables, previous studies did not incorporate all variables or identify the main contributing variables.

Greenspace exposure and academic achievement

Conversely, current literature on the presence of greenspace exposure at school and the child’s primary residence, commonly measured using satellite-based indices, is associated with an increase in student academic achievement, commonly measured by standardized test scores. Most studies observed statistically significant positive associations for at least one subject area after controlling for socioeconomics characteristics at the school level, [14–17](https://sciwheel.com/work/citation?ids=11412245,11412381,11159029,11159025&pre=&pre=&pre=&pre=&suf=&suf=&suf=&suf=&sa=0,0,0,0) although a few studies observed no association or weak negative associations. Among current literature on greenspace and AA, one of the most important research gaps is how to assess and define greenspace exposure. While most studies used satellite-based indices (e.g. NDVI, MODIS, Tree Canopy), these indices have not been evaluated for agreement, which makes comparisons between studies less precise. In addition, all studies, except for one, [18](https://sciwheel.com/work/citation?ids=11413458&pre=&suf=&sa=0) measured and analyzed data at the school level, not at the individual level. This ecological study design also leads to the measurement of confounding variables at a school level, which likely results in residual confounding. Only a few of these studies controlled for collinearity, [14,17](https://sciwheel.com/work/citation?ids=11159025,11412245&pre=&pre=&suf=&suf=&sa=0,0) an inherent issue when using multiple confounding variables. In many studies, particularly studies with a large target area, the greenspace exposure was usually taken from a single day measurement, not an average of several measurements taken over several years.

Academic achievement is an important predictor of children’s current and future success and well-being, with evidence that high academic performance at school or in college is an indicator for higher educational attainment, [4](https://sciwheel.com/work/citation?ids=11413502&pre=&suf=&sa=0) higher salaries, [5](https://sciwheel.com/work/citation?ids=11413495&pre=&suf=&sa=0),[6](https://sciwheel.com/work/citation?ids=11413498&pre=&suf=&sa=0) higher reported life satisfaction and happiness, [7](https://sciwheel.com/work/citation?ids=11413517&pre=&suf=&sa=0) and better health status as adults. [8,9](https://sciwheel.com/work/citation?ids=11413493,3542885&pre=&pre=&suf=&suf=&sa=0,0) Studies on IEQ demonstrated a positive association with academic achievement measured through school absences, [11](https://sciwheel.com/work/citation?ids=8964323&pre=&suf=&sa=0) student attendance, [12](https://sciwheel.com/work/citation?ids=8963651&pre=&suf=&sa=0) special cognitive tests [12](https://sciwheel.com/work/citation?ids=8963651&pre=&suf=&sa=0) and directly with standardized test scores. [12](https://sciwheel.com/work/citation?ids=8963651&pre=&suf=&sa=0) However, other IEQ components (e.g., thermal comfort, visual quality, acoustics) are still largely unexplored as independent factors. While some studies provided evidence that school buildings with low IEQ had low average test scores, [11,19](https://sciwheel.com/work/citation?ids=9053756,8964323&pre=&pre=&suf=&suf=&sa=0,0) individual contributions from each IEQ component have not been evaluated simultaneously. Recently, greenspace, a factor of environmental quality, was also found to have positive associations with standardized test scores in the majority of the previous studies, which used ecological study designs. To address this gap, we will evaluate this association at an individual level.

Our long-term goal is to provide guidance on school environments that promotes student well-being and performance. The specific objectives of this study are to investigate the association between both IEQ and greenspace exposure on student academic performance. We obtained a dataset with student-level demographics and test score data from the Colorado State University Health Study. We will link the student data, including the outcome student test scores, with the study exposures of interest. The exposures will include the IEQ scores, obtained from Operations Report Card (ORC) data following the Collaborative for Higher Performance Schools (CHPS), and the satellite-based indices for greenspace, obtained from Landsat 7 and National Land Cover Database. This is the first study that incorporates multiple potential IEQ exposures to identify the main contributing components affecting student academic performance while adjusting for confounding factors. We will also review and compare different greenspace measurement approaches to provide a guide for future studies requiring satellite-based vegetation indices. We will address the proposed research question by addressing the following specific aims:

1. Evaluate the association between IEQ scores from ORC and student standardized test scores for math and English/Literature, while adjusting for confounding factors. We expect to find higher standardized test scores in math and ELA among children with exposure to better IEQ based on previous literature.
2. Evaluate the agreement in measuring greenspace from different approaches found in previous literature on greenspace and students’ academic achievement. We expect the greenspace measurement approaches to have a large difference in how they are measured and defined, and which hypothesized causal pathways are appropriate. We expect the quantitative agreement analysis will show a high agreement result overall.
3. Evaluate the associations between the proportions of greenspace in areas surrounding students’ school and primary residence and their standardized test scores for math and English/Literature, while adjusting for confounding factors. We expect to observe higher standardized test scores in math and ELA among children with higher exposure to greenspace based on previous literature. Although we expect the potential confounders, particularly those related to socioeconomic status to explain a lot of the differences in standardized test scores, we do not expect them to explain the entire association based on the results from previous studies.

Innovation

While not the first one, our study measures and analyzes student academic achievement at an individual level, a preferred method over the school level that all previous studies, except for one, [18](https://sciwheel.com/work/citation?ids=11413458&pre=&suf=&sa=0) have used. This is the first study that incorporates multiple potential factors to identify the main contributing indoor environmental components affecting student academic performance while adjusting for confounding factors. While there have been qualitative comparisons and reviews of greenspace measurement approaches, our study is the first to formally evaluate these approaches with an agreement analysis.

CHAPTER II

## INDOOR ENVIRONMENTAL QUALITY SCORES AND ACADEMIC ACHIEVENMENT AMONG SCHOOL-AGE CHILDREN

To Do:

Introduction

Methods

Study population: tk schools, tk race/ethnic, gender proprotions, tk free reduced lunch %

Edit table for variables: all variables and its definition/classifications

Eligible criteria

Flow chart

Results

Discussion

Unit of analysis in previous studies

Result of previous studies

Read:

* Academic stars and Energy Stars, an assessment of student academic achievement and school building energy efficiency
* Sociodemographic variations in the association between indoor environmental quality in school buildings and student performance
* How does absenteeism impact the link between school's indoor environmental quality and student performance?

#### ABSTRACT

#### INTRODUCTION

#### METHODS

##### Study population

We will conduct a retrospective cohort study investigating the effects of IEQ and greenspace exposure on academic performance in school-age students. We will use the same source population for all three specific aims. The source population is students in the Adams 12 Five Star school district in the northern suburbs of Denver, CO. Our study population includes 55 schools with over 39,000 students (approximately 47% White students, 42% Latinx students, 5% Asian students, 2% Black/African American Students, and 1% Native American and Native Hawaiian/Pacific Islander students). Approximately 18% of students have limited English language proficiency, and almost 40% qualified for the Federal Free/Reduced Price Lunch Program. The student standardized test scores were collected for the schools in the Adams 12 Five Star district during 2015-2019.

IRB # tk

##### Data sources

We collected data from multiple sources, First, data on the study population were collected through the Colorado State University Health Study, which is partly funded by the Environmental Protection Agency. The data include IEQ measurements, student standardized test scores, student demographic, school and student residential locations. Details on these variables are provided below (Table 1). Second, using the school and student residential locations, we will link census tract-level data on demographics and socioeconomic status from the US Census American Community Survey (ACS) to obtain data on potential confounders. Third, we obtain publicly available data on school characteristics from the Colorado Department of Education (CDE) to collect data on student enrollment and percentage of free/reduced-price lunch program. In all these data sets, the only identifiers accessed was the student’s geocoded home residence.

IRB: how data was protected and secured

To link the student test score data to the school data from CDE, we used the CDE school number, a code for each school designated by the CDE. To link the student test score data to the ACS data, we geospatially overlaid the student residential location onto the census tract-level ACS data.

Table 1. Variables provided by Colorado State University for analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | **Data source** | **Data level** | **Justifications** | **Values/Classification** |
| *Classroom Measurements* |  |  |  |  |
| Temperature comfort | CSU Health | School | Exposure measurement | A score calculated from site measurement and survey, ranging 0-100 |
| Luminous Intensity | CSU Health | School | Exposure measurement | A score calculated from site measurement and survey, ranging 0-100 |
| Ambient Sound Levels | CSU Health | School | Exposure measurement | A score calculated from site measurement and survey, ranging 0-100 |
| Air quality | CSU Health | School | Exposure measurement | A score calculated from site measurement and survey, ranging 0-100 |
| Student Data |  |  |  |  |
| Age | CSU Health | Student | Important potential confounder/effect modifier |  |
| Sex | CSU Health | Student | Important potential confounder/effect modifier | Female or Male |
| The number of absences and unexcused days | CSU Health | Student | Important potential confounder/effect modifier | Discreet number depicting the number of absent/unexcused days |
| The number of instruction days | CSU Health | Student | Important potential confounder/effect modifier | Discreet number depicting the number of instruction days |
| English language learner |  | Student | Important potential confounder/effect modifier |  |
| Student test score (Math/English language arts) | CSU Health | Student | Outcome measurement | Two test scores for Math and English language arts, ranging 650-850 |
| CDE school number | CSU Health | Student | Required to link students to their schools | A code for each school designated by the Colorado Department of Education |
| Student residential location | CSU Health | Student | Required for linkage with US EPA and US Census | Longitude and latitude, in the World Geodetic System (WGS84) coordinate system |
| School Characteristics |  |  |  |  |
| The number of students | CDE | School | Important potential confounder/effect modifier | The number of K-12 students enroll in each school |
| Percentage of students participating in federal free/reduced price lunch programs | CDE | School | Important potential confounder/effect modifier | The proportions of students eligible for the federal free or reduced price lunch program |
| Percentage of students with limited English language proficiency |  | School | Important potential confounder/effect modifier |  |
| School location | CSU Health | School | Required for linkage with US EPA and US Census | Longitude and latitude |
| Socioeconomic characteristics |  |  |  |  |
|  | US Census | Census tract | Important potential confounder/effect modifier |  |
|  | US Census | Census tract | Important potential confounder/effect modifier |  |
|  | US Census |  | Important potential confounder/effect modifier |  |

Eligible Criteria

Deduplication

Students:

1. From schools with IEQ measurements
2. Instruction days of at least 145 days: (1) CDE requirement 160 days, (2) max 178 days, sd = 16 days; 85% = 151.3 days
3. Limit total day missed =

##### Exposure assessment: weighted scores for each IEQ component

The exposure of interest is the school-level scores for each IEQ component, including thermal comfort, visual quality, acoustics, and indoor air quality. The IEQ scores were obtained from Operations Report Card (ORC) data following the Collaborative for Higher Performance Schools (CHPS) template (<https://chps.net/orc>). We obtained and used the IEQ scores measured during the 2015-2016 school year.

The overall IEQ scores comprised occupant survey scores and site measurement scores and were estimated for each component. The overall IEQ scores were calculated as the average of the occupant survey score and the site measurement score for each IEQ component, as in Equation (1).

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

First, the occupant survey was emailed to and filled out by the school administrative staff and teachers. For each IEQ component section, the occupant surveys assessed occupant satisfaction using a Likert scale from 1 (very dissatisfied) to 6 (very satisfied). [Table 2](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#tab_occsurvey) provides the questionnaire by IEQ components. From the survey responses, the occupant survey score was calculated as the average of the mean satisfaction percentage and the satisfied user percentage, as in Equation [(2)](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#equ_scoreoccupantsurvey).

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

To estimate the mean satisfaction percentage, CHPS first estimated the mean of Likert scale scores from all the indicated questions and all the users at each school. The mean satisfaction percentages were the conversion of the mean of Likert scale scores (ranging from 1 to 6) to percentages (ranging from 0 to 100). The conversion formula was in Equation [(3)](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#equ_scoremeansatisfactionpct). From this formula, a six becomes 100, one becomes 0, and 3.5 (the median of the range from 1 – 6) becomes 50.

|  |  |  |
| --- | --- | --- |
|  |  | (3) |

The satisfied user percentage was the percent of users satisfied across all indicated questions, as in Equation [(4)](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#equ_satisfieduserpct).

|  |  |  |
| --- | --- | --- |
|  |  | (4) |

Second, the site measurement score was constructed from the measurement collected at the site by the school custodians and maintenance staff. [Table 3](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#tab_IEQmeasurement) provides the parameter, measure, and equipment for the measurement of each IEQ component. These measurements were then classified into 3 acceptability groups: “acceptable”, “possibly unacceptable”, and “unacceptable”. [Table 4](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#tab_acceptabilitycat) provides the acceptability ranges by IEQ component. The site measurement weighted score was calculated as the sum of the “acceptable” percentage and half of the “possibly unacceptable” percentage, as in Equation [(5)](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#equ_scoresitemeasurement).

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

Finally, the occupant survey score and the site measurement score for each IEQ component were averaged to estimate the IEQ scores, as in [(1)](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#equ_scoreoverall) above. These overall IEQ scores for different components () were our exposure measurement of interest that would be used in the analyses.

Table 2. Questions from the occupant surveys by indoor environmental quality (IEQ) component.

|  |  |
| --- | --- |
| **IEQ Component** | **Questions** |
| Thermal comfort | Overall, how satisfied are you with the temperature in your classroom?  How satisfied are you with how the following equipment operates (if present)?  Thermostat  Air Conditioner  Heater  Windows  Doors |
| Visual Comfort | Overall, how satisfied are you with the lighting in your space?  Overall, how satisfied are you with the electric lighting in your space?  Overall, how satisfied are you with the amount of natural light (daylight) in your space? |
| Acoustics | Overall, how satisfied are you with the acoustics (sound quality) in your classroom?  How disruptive are the following potential noise sources in your space?  Echoes within the room.  Outside traffic  Outside playground noise  Hallway noise  Neighboring classrooms  Mechanical equipment (air conditioners, fans, etc.) |
| Indoor Air Quality | Overall, how satisfied are you with the indoor air quality in your classroom?  How stuffy do you consider the air in your space?  How satisfied are you with how your space generally smells? |

Table 3. Indoor environmental quality measured and its corresponding equipment and locations.

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** | **Measure** | **Equipment** | **Measurement Note** |
| Thermal Comfort | Temperature | Extech CO2/T/RH\* | It was measured four times throughout the day in five different locations within the classroom. |
| Humidity | Extech CO2/T/RH |  |
| Visual Quality | Luminous Intensity | General Tools DLM204 Digital Light Meter | It was measured in different areas in the classroom four times a day |
| Acoustics | Ambient Sound Levels | NTi AL1 Acoustilyzer | It was measured in the test classroom, as well as the adjacent classroom and hallway, while accounting for room sound reverberation. |
| Indoor Air Quality | CO2 | Extech CO2/T/RH | It was measured at select air return and air supply vents in the classrooms, collected at three different times of school day. |
| CO | General Tools DCO1001 CO Meter |
| \*Extech Carbon Dioxide, Humidity, and Temperature Data Logger | | | |

Table 4. Acceptability classification for site measurement by indoor environmental quality component.

|  |  |  |  |
| --- | --- | --- | --- |
| **Item** | **Acceptable** | **Possibly Unacceptable** | **Unacceptable** |
| Thermal Comfort | | | |
| Heating Set Point (occupied mode) | 68 – 74.5°F | [none] | < 68°F  >74.5°F |
| Heating Set Point (unoccupied mode) | 55 - 65°F | 65 - 68°F | > 68°F |
| Cooling Set Point (occupied mode) | 73 – 79°F | [none] | < 73°F  > 79°F |
| Cooling Set Point (unoccupied mode) | 82 - 85°F | 78 - 81°F | < 78°F |
| Recorded Occupied Temperature | Within 2°F of setpoint | Within 2 - 4°F of setpoint | Outside 4°F of setpoint |
| Visual Comfort |  |  |  |
| Minimum Illumination Level | ≥ 35 fc | 25 – 34 fc | < 25 fc |
| Maximum Illumination Level | ≤ 50 fc | 51 – 60 fc | > 60 fc |
| Average Illumination Level | 35 – 50 fc | 25 – 34 fc  51 – 60 fc | < 25 fc  > 60 fc |
| Acoustics | | | |
| Background Noise | ≤ 35 dBA | 36 – 45 dBA | > 45 dBA |
| Sound Insulation (classroom to classroom) | ≥45 dB | 35 – 44 dBA | < 35 dBA |
| Sound Insulation (classroom to hallway) | ≥40 dB | 39 – 30 dBA | < 30 dBA |
| Indoor Air Quality | | | |
| Carbon Dioxide (CO2) | ≤ 700 ppm above outdoor levels | > 700 ppm above outdoor levels | > 2000 ppm total (not above outdoor levels) |
| Carbon Monoxide (CO) | ≤ outdoor levels | > outdoor levels | > 35 ppm total |
| Temperature (measured while HVAC in occupied mode) | Cooling: 73 – 79°F  Heating: 68 – 74.5°F | [none] | Outside acceptable ranges |
| Relative Humidity | 30% - 60% | < 30%  61% - 69% | ≥ 70% |

##### Outcome assessment: academic performance

The outcome of this study, the student academic performance, will be assessed with annual standardized scaled test scores. We will use 2015-2019 test score data from the Partnership for Assessment of Readiness for College and Careers (PARCC), a consortium of states including Colorado. [20](https://sciwheel.com/work/citation?ids=10717359&pre=&suf=&sa=0) The PARCC test scores are based on the learning standards from the Common Core State Standards; these are K-12 English language arts (ELA) and mathematics (MTH) standards establishing clear and consistent goals for learning and have been adopted by 45 states and the District of Columbia.[20](https://sciwheel.com/work/citation?ids=10717359&pre=&suf=&sa=0) For each standard, a scale score and a performance level are reported for each student in each year. The scale score is a continuous measurement ranging from 650 to 850, which is standardized to ensure comparability across test forms and administration years within a grade or course and content area. The scale score can also be used to assign the students to 5 performance levels: (1) Did not yet meet expectations, (2) Partially met expectations, (3) Approached expectations, (4) Met expectations, and (5) Exceeded expectations. Students with performance levels of 4 or 5 are considered to be on track for college and careers and ready for the next grade. [21](https://sciwheel.com/work/citation?ids=10717355&pre=&suf=&sa=0)

##### Covariate assessment

From previous literature on measured IEQ and academic achievement, we will aggregate all potential confounding variables. Since very few previous studies on IEQ and academic performance addressed confounding, we will also identify confounding variables based on subject matter knowledge. From these potential confounders, we will build a DAG to explicitly represent our assumptions on the relationship among these variables, the IEQ exposure, and the academic achievement in students. We will use previous literature to guide these relationships; when not available, we will evaluate different scenarios to account for these unclear relationships.

Table. Confounding variables or effect modifiers from previous studies

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Study | Study design | Exposure | Outcome | Potential covariates | Confounding variables | Effect modifiers |
| Benlojevic et al. 20121 | Cross-sectional | Noise level | Cognitive Skills (Executive functioning) | Student level: Age, SES index (mother’s  highest education & perceived family income), number of family members per dwelling, hours child spends indoors | SES index (mother’s  highest education & perceived family income) | Gender |
| Dockrell & Shield 20062 | Experimental | 3 Noise conditions | Cognitive Skills (Aptitude, verbal, & arithmetic tests) | None | None | None |
| Hygge 20033 | Experimental | Noise vs quiet conditions | Cognitive Skills (text reading: recall & recognition) | None | None | None |
| Stansfeld et al. 20054 | Cross-sectional | External aircraft and road traffic noise at school | standardized tests and Cognitive Skills (questionnaires) | Student level: SES status (employment status, housing tenure, crowding), maternal education, ethnic origin, main language spoken at home | age, sex, country  socioeconomic status  and mother’s education  children’s longstanding illness, main language  spoken at home, parental support for schoolwork, and  the type of glazing in the windows of the child’s  classroom | Explore: SES variables  Found: crowding home |
| Haines et al. 20015 | Cross-sectional | High noise vs. control | Standardized Tests (reading comprehension) & Cognitive Skills | Matched: (a) age of the  children; (b) sound level at the school from nonaircraft sources; (c) the extent of existing noise  protection in the schools  Potential: household deprivation score (income, crowding, home ownership and unemployment), main language spoken at home, age | age (at the time of testing); main language  spoken at home (English and non-English); household deprivation (deprived and non-deprived) |  |
| Matheson et al., 20106 | Cross-sectional | Chronic aircraft noise exposure | Cognitive Skills (classroom-based tests of cued recall, recognition memory and prospective memory) | matched according to socioeconomic position, number of pupils eligible for free school meals and main language spoken at home beginning with those schools exposed to the highest levels of aircraft noise | classroom glazing, i.e., the type of windows in the child's classroom, age, sex, country, mother's educational attainment, socioeconomic status which was measured by employment status, crowding and home ownership, LSI, main language spoken at home and parental support for school work and the other noise exposure variable, e.g., for aircraft noise analyses, road traffic noise exposure, parental report of the child having dyslexia and acute noise during testing |  |
| Maxwell &  Evans, 2000 | Cohort model? | the installation of sound absorbent panels | cognitive measures of pre-reading skills ((1) number and letter recognition, (2)  letter-sound correspondence, and (3) rhyming) | None | None | None |
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|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Study | Study design | Exposure | Outcome | Potential covariates | Confounding variables | Effect modifiers |
| Haverinen-Shaughnessy & Shaughnessy, 20157 | Cross-sectional | indoor temperature (T), relative humidity (RH), and carbon dioxide (CO2)  to estimate: ventilation rate & temperature | statewide mathematics score | class size (i.e. number of students in the classroom) and school level  socioeconomic variables (e.g. percent of student eligible for free lunch) | gifted status, limited  English proficiency, ethnic group, mobility, eligibility to free or reduced lunch, gender, the  composite variable ‘number of days absent, no illness’, teacher’s highest degree | Ethnic group, Eligibility to free lunch, Gifted, English |
| Haverinen-Shaughnessy et al., 20158 | Cross-sectional | temperature (T), relative humidity (RH), carbon dioxide (CO2), and settled dust.  to estimate: ventilation rate & temperature | % satisfactory math/reading scores  (also absenteeism, health) | School-level: percent of students by different ethnic groups (Native American, Asian, African American,Hispanic and Caucasian), gender, gifted or talented, eligible for free or reduced lunch, and limited English proficiency. | None | None |
| Park, 2016 | Cross-sectional | Outdoor temperature from closest weather station on days of exam | Regents exam scores | None | None | None |
| Park et al., 2020 | Cross-sectional | the school-level average maximum temperature experienced during school days in 365 days prior to the test | PSAT |  | prior year rainfall and snowfall, test day temperature, rainfall, snowfall  prior year and test day pollution  levels (carbon monoxide, ozone, suflur dioxide, nitrogen dioxide, and PM10)  the logarithm  of per capita county-level payroll in industries highly exposed to weather  state-specific linear time  trends | None |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Study | Study design | Exposure | Outcome | Potential covariates | Confounding variables | Effect modifiers |
| Dahlan & Eissa, 20059 | Cross-sectional | Daylighting (illumination in lux) | GPA | None | None | None |
| Govén et al., 201110 | Experimental study | a general lighting system adjusted to an illuminance level at working plane of approximately 500 lx | School tests (Reading & Math), Mood, Sleep self report, absenteeism, melatonin level, | None | None | None |
| Hathaway, 199511 | Quasi-experimental study | Type of lighting (different light spectrum, with/without UV) | Canadian Test of Basic  Skills (15  measures: vocabulary, reading, language (four tests and a subscore), work study (two tests and a subscore),  mathematics (three tests and a subscore), and a total score) | None | None | None |
| Heschong et al., 200312 | Cross-sectional | Daylight Code (scalar 0−5): 0=no daylight, 5= maximum condition  Other light related (Window orientation, area, tint, view, sun penetration, glare, security measures on window, blinds/curtains, operable windows, exterior doors)  Electric light  (Indirect luminaire , Luminaire condition, Ballast type, Lamp color, Electric illuminance, Lamp type)  Other IEQ (IAQ, Noise) | standardized math and reading  tests |  | Teacher characteristics (Annual salary of teachers, Number of years, Mentor, Pre-tenure, Multi-grade classroom)  Student characteristics (Grade level, Percentage attendance, Qualified for/enrolled in GATE (Gifted and Talented Education), Special Education student, English Language development level, Free lunch, Lowest income students, Reduced lunch, Low income student, Non-standard living situation, Student gender, Ethnic)  School parent education | None |
| Heschong et al., 1999 |  | Daylight Code,  Window Code,  Skylight Code,  Skylight Types,  AC, AC types, Operable Windows, Classroom type | Standardize test score (NCE/RIT scale) | School Operation (Language Program,  Year Round Schedule, Students per School, Students per Classroom, Age of School: yrs since original construction)  Student Characteristics (Grade level, Classroom assignment, Ethnicity, Special Education program, Non-English speaking, GATE identified)  Student level (Gifted classroom, Lunch Program, Living w/ mother, father, other, Gender, Absences Unverified, Absences Unexcused, Number of Tardies | Grade Level, GATE Program School Site, Operable Windows, Language Program, Absences,  School population,  Ethic, gifted room, grade, school population, students per class, economic & social status, portable classrooms, open classrooms, school square feet | Evaluate: school size, unverified absenteeism, unexcused absenteeism, the gate program, the language program, and the three grade level indicator variables.  Found: None |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Study | Study design | Exposure | Outcome | Potential covariates | Confounding variables | Effect modifiers |
| Kabirikopaei et al., 202113 | Cross-sectional | Occupied  Measurements: CO2, formaldehyde, fine particles (0.3–2.5  μm), and coarse particles (2.5–10 μm). Unoccupied measurements:  air velocity, CO, NO2, O3, and TVOC. | Classroom aggregated scores in mathematics and reading | classroom-aggregated  percentages of free and reduced lunch recipients (PFRL), high-performance (or gifted) students (PGIF), and special  education students (PSPED) | classroom-aggregated  percentages of free and reduced lunch recipients (PFRL), high-performance (or gifted) students (PGIF), and special  education students (PSPED) | Explore: classroom-aggregated  percentages of free and reduced lunch recipients (PFRL), high-performance (or gifted) students (PGIF), and special  education students (PSPED)  Found: None |
| Toyinbo et al., 201614 | Cross-sectional | Indoor temperatures  Exhaust air flow or carbon dioxide (CO2) measurements | National learning assessment test for mathematics | Student level: socioeconomic status (SES) and background variables | Attitude towards mathematics, first language, mother’s education, father’s education, take naps during the day, gifted in mathematics, gifted linguistically, gifted in sports, needs personal tutoring regularly | None |
| Toftum et al., 201515 | Cross-sectional | CO2 concentration | Class-level Danish national standardized test scores | socioeconomic reference index (based on gender, age, ethnicity and country of origin, parents' highest level of education, parents' income, employment, family status (couple, single), number of children in the family and rank of the child, and interaction between gender and ethnicity)  building related characteristics: person specific room volume, construction/renovation year, occupancy, window opening frequency and window orientation | socioeconomic reference index (based on gender, age, ethnicity and country of origin, parents' highest level of education, parents' income, employment, family status (couple, single), number of children in the family and rank of the child, and interaction between gender and ethnicity)  building related characteristics: person specific room volume, construction/renovation year, occupancy, window opening frequency and window orientation | None |
| Mendell, 201616 | Cross-sectional | Daily VRs were estimated from  indoor carbon dioxide (CO2) concentrations | Standardized Testing and Reporting (STAR) test scores in Math and English | Classroom-level: participation in free or reduced-price meal program, English-learner status, gifted status, special education status, gender, and race/ethnicity. | Prior year test scores  Gender, ethnicity, gifted status, special education status, and participation in free or reduced-price meals. | None |
| Haverinen-Shaughnessy et al., 20158 | Cross-sectional | temperature (T), relative humidity (RH), carbon dioxide (CO2), and settled dust | School-level the percentages of students scoring satisfactory | School-level: percent of students by different ethnic groups (Native American, Asian, African American,Hispanic and Caucasian), gender, gifted or talented, eligible for free or reduced lunch, and limited English proficiency. | None | None |
| Haverinen-Shaughnessy et al., 201117 | Cross-sectional | Indoor CO2 concentration | Classroom-level percent of students scoring satisfactory or above in  math and reading tests | classroom level:  mobility rate, percent limited English (English language learners), free lunch program participants (economically disadvantaged), and gifted enrollment.  %Asian, %White | classroom level:  mobility rate, percent limited English (English language learners), free lunch program participants (economically disadvantaged), and gifted enrollment.  %Asian, %White | None |
| Stafford, 201518 | Quasi-natural-experiment | Type of renovations (before & after) | Standardized test scores in math and reading |  | (i) homeroom class size, (ii) homeroom  teacher's years of experience within the district, (iii) homeroom teacher's annual salary | None |
| Shaughnessy et al, 200619 | Cross-sectional | CO2 concentrations to estimate ventilation rate | Standardized test scores in math and reading | Classroom level: male/female ratio, attendance rate, and % free lunch program participants (for indication of family income), % gifted enrolment (for indication of the extent to which each class was selective for gifted students), % mobility rate (for indication of the extent to which the students attending the class remained the same through the school year) and % limited English (for indication of cultural/lingual effects) | Math scores: % free lunch, % limited  English, and % mobility rate  Reading scores: % free lunch, % mobility rate, % gifted enrollment,  and % limited English | None |
| Haverinen-Shaughnessy & Shaughnessy, 20157 | Cross-sectional | indoor temperature (T), relative humidity (RH), and carbon dioxide (CO2)  to estimate: ventilation rate & temperature | statewide mathematics score | class size (i.e. number of students in the classroom) and school level  socioeconomic variables (e.g. percent of student eligible for free lunch) | gifted status, limited  English proficiency, ethnic group, mobility, eligibility to free or reduced lunch, gender, the  composite variable ‘number of days absent, no illness’, teacher’s highest degree | Ethnic group, Eligibility to free lunch, Gifted, English |
|  |  |  |  |  |  |  |

We obtained socioeconomic characteristics data at the census tract level from US Census American Survey (ACS). Since the student test scores were during 2015-2019, we used the ACS 2015-2019 5-year estimate, which is the average of the same period as the test score data. To represent socioeconomic characteristics, we constructed the variables for the analysis using the variables from ACS. We used the variables from the Social Vulnerability Index (SVI) to construct our variables. The Social Vulnerability Index (SVI) database was created by the Center for Disease Control and Prevention to describe geographic areas in the United States ranked according to their social vulnerability. SVI ranking had four themes: socioeconomic status, household composition and disability, minority status and language, and housing and transportation. Multiple variables were used under each theme. In our study, we did not include all variables from the SVI, nor did we use the SVI for the analysis. We only applied their variable constructions to reconstruct necessary variables for our study.

The ACS estimates were grouped into multiple broad categorization called “concept.” Each concept has a code for easy identification. These codes remained the same across the years. For each concept, there are multiple estimates, which usually included an estimates for the total population and estimates for the subgroups of the concept. For example, to calculate the proportions of renter-occupied households, we used the concept “Tenure,” which had the code as “B25003.” In this concept, there were 3 estimates: the total households, the number of owner-occupied households, and the number of renter-occupied households. For each census tract, the proportion of renter-occupied households was calculated as the ratio of the number of renter-occupied households and the total households. Table X provided details on how each variable was constructed.

Constructed variables for socioeconomic characteristics from variables from US Census American Survey 2019 5-year estimates.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Constructed variables | Census variable name | Census variable concept | Numerator | Denominator |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |

We obtained school characteristic data from publicly available data sets on the website of the Colorado Department of Education. The variables of interest were student enrollment (defined as the number of K-12 students recorded) and the percentage of free/reduced-price lunch program (defined as the proportions of students eligible for the federal free or reduced-price lunch programs). These estimates were available for each year. Therefore, we calculated an average for four academic years in 2015-2019 as our estimates for the analysis.

For the school-level data, we could also calculate the ACS variable estimates for each school; these ACS estimates would be calculated as the mean/median of the estimates from the census tracts in each school boundary attendance. However, these ACS estimates would reflect the census tracts in the school attendance boundary, but not the student body of each school. This was because each census tract contributed different number of students. At the same time, the percentage of free/reduced-price lunch program is a commonly used variable that reflects socioeconomic status of the student body (tk: cite)

##### Statistical analysis

We will describe the IEQ measurements, test scores, and covariates using the central tendency (mean, median) and variability statistics (standard deviation and quantiles). For the multivariable analysis, we will use a multilevel mixed-effect model. The dependent variables, standardized PARCC scaled test scores, are expected to be continuous and normally distributed. The main independent variables are the school-level scores for each IEQ component, including thermal comfort, visual quality, acoustics, and indoor air quality. Our model will account for correlation among students within the same school and within the same census tract using the random effect method. Since school and census tract were not nested in each other, our model was a cross-level model. (tk: cite) To control for potential collinearity between independent variables, we will examine correlation matrix and correlation network to identify correlated variables. We retained only one variable in each groups of highly correlated variables (correlation coefficient of more than 0.80) based on their strength of association with the outcome and their presence in previous studies.

In the bivariate analysis, we will model the outcomes with each independent variable using mixed model regression accounting for school and census tract correlation. We evaluated the normality assumptions with the QQ plots and residual histogram. Deviations from the 45-degree line in the QQ plots or a bell-shaped curve in the residual histogram showed signs of normality violation. We evaluated homoscedasticity assumptions using residual plots. A funnel shape pattern in the plots between the standardized residuals and predicted outcomes or non-linear trends in the plots between the absolute of the standardized residuals and the predicted outcomes showed signs of homoscedasticity violations. We evaluated linearity assumption using the scatter plots with overall loess curves. Variables deviated from a linear trend on the scatterplots will be considered non-linear and categorized based on the quantile and the loess curve. We evaluated the both clinical significance and statistical significance in the bivariate analysis. A p-value of less than 0.05 indicated a statistical significance. A product of the beta-coefficient and range (maximum minus minimum) of the variables that was greater than the SD of the outcome indicated a clinical significance. Variables for student characteristic, school characteristic, and census-tract-level SES which were clinically and statistically significant in the bivariate analysis will be considered for the multiple variable regression

We will build the multiple variable model in 2 stages. First, we model the outcome, test scores, with the covariates and the school ID. This model result will reflect the contribution from the covariates and the cluster effect on the test scores. Second, we will include the school-level IEQ scores. The school-level IEQ scores will be modeled individually and then combined in a final model.

Since the outcome (scale test scores) cannot be compared across grades, we can only build a model for each grade. We will consider using one grade for each school level (elementary, middle, and high school). We will also build a model with a different grade, then use the data from a consecutive grade (within the same school level) to validate the model; this additional model validation will help strengthen our study results.

To compare with previous study results which analyzed the relationship between test scores and IEQ at the school-level, we also aggregated our student-level data to school-level data and conducted regression analysis. Due to the small number of schools (33 elementary schools), we used a nonparametric approach, quantile regression. Quantile regression does not assume any distribution of the data and is robust to outliers (tk: cite). For the quantile regression, we used tau (quantile) = 0.50 to model the median of the test scores in relation to the independent variables.

All analyses will be conducted using the R statistical software.

#### RESULTS

We have tkXXX students with test score measurement. After deduplication, we removed tkxxx students. We removed tkxxx students whose school did not have IEQ measurements. We limit the instruction days to 145, removing tkxxx students. We limited by total missed day of, removing tkxxx students. Our final sample size is tkxxx

##### Descriptive Statistics Summary

Our study population from grade tkxxx has this tkxxx% female, race

Our study population from grad tkxxx middle school

Our study population from grade 9 has this tkxxx% female

Table 5. Descriptive statistics summary of demographic and socioeconomic characteristics, indoor environmental quality components, and standardized test scores for study participants.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Grade E  (n=) | Grade M  (n=) | Grade H  (n=) |
|  | n (%) | n (%) | n (%) |
| Sex  female  male |  |  |  |
| Race/Ethnicity  Non-Hispanic Black  Asian/Pacific Islander  Non-Hispanic White  Latinx  Other |  |  |  |
|  | Mean (SD) | Mean (SD) | Mean (SD) |
|  |  |  |  |
| Age (years) |  |  |  |
| Absent Days |  |  |  |
| Unexcused Days |  |  |  |
| Free Lunch (%) |  |  |  |
| Reduced Lunch (%) |  |  |  |
| Median Household Income (x $10,000) |  |  |  |
| Percent Uninsured (%) |  |  |  |
| ORC |  |  |  |
| Energy |  |  |  |
| Thermal |  |  |  |
| Acoustics |  |  |  |
| Visual |  |  |  |
| Indoor |  |  |  |
| Standardized test scores |  |  |  |
| Math |  |  |  |
| English language arts (ELA) |  |  |  |

##### Bivariate Mixed-Model Regression Results

##### Multiple Variable Mixed-Model Regression Results

##### School-Level Quantile Regression Result

#### DISCUSSION

Reiterate problem

Reiterate your findings

Nest your findings in the broader literature: evaluate what’s new, what’s concordant, what’s discordant

Nest findings in what is known about the mechanisms about the exposure-disease relationship

Evidence that absenteeism does not mediate IEQ and test scores (tk: bonnie 2021). IEQ affect absenteeism but not test score in our study population

Implication for findings (policy, practice, treatment, intervention)

SES and student characteristics are more influential on test scores than the IEQ

Implication for future studies

Study strengths

The main strength of this aim is the integrated approach for exposure assessment. By evaluating multiple exposures, we can assess the contributing portion of individual exposures, as well as the interactions among them. In addition, this will be the first study to evaluate the confounding effect and their assumptions explicitly through the use of a DAG. The outcome, test scores, is measured at an individual level, unlike most of the previous studies; this detailed information can provide a better inference and avoid ecological fallacy.

Study limitations

There are, however, still limitations in our approach. First, the outcome unit of measurement is an individual, but the exposure unit of measurement is a school. Compared to previous literature, which has both exposure and outcome measured at the school level, our study still has more detailed information even with the school-level IEQ scores as the exposure. Second, the IEQ scores are not a direct measurement of the environment (e.g, degree Celsius for temperature); rather, IEQ scores were constructed based on both direct site measurement and occupant satisfaction survey. Therefore, while it is not easily comparable to other studies, our interpretation of the results will still be helpful for comparing school building conditions, particularly in schools that also use similar ORC IEQ scores. Third, some of the potential confounders in our study will be measured at a census-tract level by linking student residential addresses to additional data sources. We expect residual confounding due to this use of census-tract level variables. However, it is important to note that these confounders are still measured at a more detailed level than previous studies (at the school level) and we expect that the results will provide additional information on the effect of these confounders on our main association of interest. Finally, although our dataset contains data from the same groups of students through multiple years, we were not able to conduct a longitudinal study. This is because the outcome, scale test scores, were not designed to compare students across grades, only students in the same subject across different administrative years

Conclusion

CHAPTER III

## COMPARISON OF GREENSPACE MEASUREMENT APPROACHES

#### ABSTRACT

#### INTRODUCTION

#### METHODS

##### Study design

We will conduct a review and agreement assessment study on the measurement of greenspace exposure. We will identify studies in the greenspace and academic achievement literature and extract all relevant greenspace measurement approaches to compare. We will compare these approaches qualitatively and quantitatively.

##### Study population

* 1. Study Population Overview

We will conduct a retrospective cohort study investigating the effects of IEQ and greenspace exposure on academic performance in school-age students. We will use the same source population for all three specific aims. The source population is students in the Adams 12 Five Star school district in the northern suburbs of Denver, CO. Our study population includes 55 schools with over 39,000 students (approximately 47% White students, 42% Latinx students, 5% Asian students, 2% Black/African American Students, and 1% Native American and Native Hawaiian/Pacific Islander students). Approximately 18% of students have limited English language proficiency, and almost 40% qualified for the Federal Free/Reduced Price Lunch Program. The student standardized test scores were collected for the schools in the Adams 12 Five Star district during 2015-2019.

##### Data sources

Data on the source population were collected through the Colorado State University Health Study, which is partly funded by the Environmental Protection Agency. The data include IEQ measurements, student demographics, and residential locations. Details on these variables are provided ([Table 1](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#tab_varlist)). Using the school and student residential locations, we will link census tract-level data on environmental quality, demographics, and socioeconomic status from the US EPA Air Data and US Census American Community Survey to obtain data on potential confounders. The only identifiers accessed include the student’s geocoded home residence. Data for the exposure and outcome in each specific aim will be described in their corresponding section.

##### Greenspace measurement approaches

We will identify appropriate greenspace measurement approaches from previous literature on greenspace and academic achievement. In collaboration with a librarian, we will conduct a literature search for relevant articles. We will use keywords representing the exposure (e.g., “greenspace,” “green space,” “greenness,” “green,” “tree\*,” “vegetation,” “landscapes”), the outcome (e.g., “achievement,” “performance,” “test score\*”) and the population (e.g., “academic,” “school\*,” “student\*”). To identify additional articles, we will use the snowball method (reviewing the references of included articles) and the visual tool Connected Papers (<https://www.connectedpapers.com>).

The eligibility criterion for these approaches is that they have to have data publicly available for at least the whole US. This criterion can ensure that (1) the data is available for our study area, Denver, CO, and (2) the results from these agreement analyses can guide future studies on greenspace in the US.

From preliminary literature search results, we have identified the following eligible approaches to measure greenspace (1) Landsat NDVI, (2) NLCD Tree Canopy, and (3) Terra MODIS Veg Index.

##### Qualitative comparison

We conduct a qualitative comparison of the different greenspace measurement approaches to help researchers decide which greenspace measurement approach to use. We identify criteria including resolution, buffer radii used in previous studies, measurement frequency, collected time, where to obtain the data, how the measurement is defined, and the matching greenspace hypothesis.

##### Quantitative agreement analysis

We will measure the greenspace exposure among our study population, students in the Adams school district, Denver, CO, using the three approaches mentioned above. The greenspace measurement will be the proportion of greenspace within buffers around the school perimeter and the student residence from 2015-2019. The buffers will have radii of 25m, 100m, 250m, 500m, and 1000m; we chose these radii as they are commonly used buffer radii from previous studies. We will quantitatively evaluate these greenspace measurements for their agreement using multiple agreement statistics and tests. Since there are three greenspace measurement approaches, we will compare them pairwise, leading to three pairs of comparison for each analysis. First, we will test for a systematic difference using paired t-tests or Wilcoxon signed ranks tests, if the normality assumption is violated. [22](https://sciwheel.com/work/citation?ids=2324183&pre=&suf=&sa=0) The null hypothesis is that the true mean/median difference is zero. Second, we will calculate the correlation coefficients using both intraclass correlation coefficients (ICC) and Lin’s concordance correlation coefficient (CCC). We will use ICC because it is a commonly used correlation coefficient. In our study, ICC is the ratio of between-method variance to the total variance (sum of the between-method variance and the between-subject variance). However, ICC can be influenced by an extremely high or low ratio of the between-method variance and the between-subject variance. [23](https://sciwheel.com/work/citation?ids=11421417&pre=&suf=&sa=0) Therefore, we will include CCC, a correlation coefficient that is more robust to these extreme ratios. [23](https://sciwheel.com/work/citation?ids=11421417&pre=&suf=&sa=0) Additionally, ICC requires ANOVA model assumptions as it used in an ANOVA model to estimate (e.g., normality assumption, equal variance assumption); the CCC does not. [24](https://sciwheel.com/work/citation?ids=222500&pre=&suf=&sa=0) Third, we will create Bland-Altman plots for visual assessment of the agreement and estimate the 95% confidence limits of agreement. Finally, we will calculate the coverage probability (CP) for agreement. CP is the probability that the absolute difference between the two measurements made on the same subject is less than or equal to a pre-specified difference. [23](https://sciwheel.com/work/citation?ids=11421417&pre=&suf=&sa=0) Since there is no previous literature on a tolerable difference in greenspace, we decided to use 5% and 10% difference in the proportion of greenspace as the pre-specified difference.

#### RESULTS

##### Qualitative comparison

Table 5 shows the qualitative comparison table, which includes initial information identified for the three greenspace measurement methods.

Table 6. Qualitative comparisons of different greenspace measurement approaches from the greenspace-academic achievement literature.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Landsat NDVI** | **NCLD Tree Canopy** | **Terra MODIS Veg Index** |
| Resolution | 30m | 30m | 250m |
| Measured Buffer Radii | 25m  250m  400m  800m  1000m  1600m  3200m  4800m | 25m  250m  1000m | 250m  500m  1000m  2000m |
| Measurement Frequency | Every 16 day | 2011, 2016 | Every 16 day  (Maybe every 2 days) |
| Collected Time | Landsat 7: 2003-present  Landsat 8: | 2011 & 2016 | 2000-02-18 to Present |
| Data Download Location | TBD | TBD | TBD |
| Measurement Description | TBD | TBD | TBD |
| Matching Hypothesis | TBD | TBD | TBD |

##### Quantitative agreement analysis

#### DISCUSSION

CHAPTER IV

## GREENSPACE EXPOSURE AND ACADEMIC ACHIEVENMENT AMONG SCHOOL-AGE CHILDREN

#### ABSTRACT

#### INTRODUCTION

#### METHODS

##### Study population

* 1. Study Population Overview

We will conduct a retrospective cohort study investigating the effects of IEQ and greenspace exposure on academic performance in school-age students. We will use the same source population for all three specific aims. The source population is students in the Adams 12 Five Star school district in the northern suburbs of Denver, CO. Our study population includes 55 schools with over 39,000 students (approximately 47% White students, 42% Latinx students, 5% Asian students, 2% Black/African American Students, and 1% Native American and Native Hawaiian/Pacific Islander students). Approximately 18% of students have limited English language proficiency, and almost 40% qualified for the Federal Free/Reduced Price Lunch Program. The student standardized test scores were collected for the schools in the Adams 12 Five Star district during 2015-2019.

##### Data sources

Data on the source population were collected through the Colorado State University Health Study, which is partly funded by the Environmental Protection Agency. The data include IEQ measurements, student demographics, and residential locations. Details on these variables are provided ([Table 1](https://docs.google.com/document/d/1reEWsCNPv2619GmplBEleYlo1eR6DIEPSHHPMDCx5Ks/edit#tab_varlist)). Using the school and student residential locations, we will link census tract-level data on environmental quality, demographics, and socioeconomic status from the US EPA Air Data and US Census American Community Survey to obtain data on potential confounders. The only identifiers accessed include the student’s geocoded home residence. Data for the exposure and outcome in each specific aim will be described in their corresponding section.

##### Exposure assessment: Greenspace

We will use two measures for greenspace: overall greenness and greenspace areas accessible to students. First, we will measure overall greenness using Landsat 8 data obtained from the USGS at the 30m2 spatial resolution. From this dataset, normalized difference vegetative index (NDVI) is calculated using the data for red and infrared wavelengths. The NDVI index ranges from -1 to +1, where −1.0 is water, 0.0 is ice, snow, barren area, or rock, and 1.0 is abundant leafy green vegetation. In addition, we will measure the greenspace areas opened to the public and can be accessed by the students using the data from the National Land Cover Database.

For both of these datasets, we plan to use the most recent data before and/or during the outcome measurement, the 2015-2019 test scores. To minimize the variability of greenness between different years, we will use an average of 5-year NDVI values. For the greenspace measure using 2013 NLCD, we will make the assumption that the greenspace areas do not change dramatically within the study time frame and will only use the most recent data before 2015.

We hypothesize that the greenspace affects the student’s academic achievement through its visual and direct interaction with the students. Therefore, we will create walking-distance buffers around the school perimeter and the student residence. We will create buffers with radii of 25m, 100m, and 500m, which we based on appropriate walking and viewing distances. Given that students at different ages will have a different average walkability distance, we will analyze students in elementary, middle, or high school separately.

##### Outcome assessment: academic performance

This outcome measurement is similar to the outcome measurement in the specific aim 1.

##### Covariate assessment

From previous literature on greenness and academic achievement, we will aggregate all potential confounding variables. From these potential confounders, we will build a DAG to explicitly represent our assumptions on the relationship among these variables, the greenspace exposure, and academic achievement in students. We plan to use previous literature to guide us on these relationships; when it is not available, we will evaluate different scenarios to account for these unclear relationships.

From a preliminary literature review, we identified many confounding variables falling into three main categories: demographic and socioeconomic characteristics, school characteristics, and outdoor environmental quality.

The demographic and socioeconomic characteristics category include race, ethnicity, financial status, educational attainment, urbanity, employment, and other variables indicating the disadvantage in academic achievement. The school characteristics category includes attendance rate, school-wide enrollment (i.e., school size), proportions of students who have limited English proficiency, student-teacher ratio, average class size, proportions of students who are in a special education program, and other variables indicating the availability of resources for student learning. The outdoor environmental quality category was used in only one previous study where their justification was that air pollution is highly associated with student academic achievement. [25](https://sciwheel.com/work/citation?ids=11421395&pre=&suf=&sa=0)

While confounding effects on the relationship between greenness and academic achievement have been explored in previous studies, albeit not rigorously, effect modification of this relationship was not commonly addressed. Only two variables have been explored as potential effect modifiers–urbanicity and sex–and no consensus findings have been reached. For urbanity, a study in California public schools identified that urban schools benefit from greenspace more than rural schools. [26](https://sciwheel.com/work/citation?ids=7094936&pre=&suf=&sa=0) However, a study in Germany found no effect modification from urbanicity on this relationship. [25](https://sciwheel.com/work/citation?ids=11421395&pre=&suf=&sa=0) For the variable sex, two recent studies found no effect modification; [25,27](https://sciwheel.com/work/citation?ids=11421395,9880572&pre=&pre=&suf=&suf=&sa=0,0) a third study identified that schools with more females benefited from greenspace. [28](https://sciwheel.com/work/citation?ids=5073122&pre=&suf=&sa=0) As there is no consensus on effect modification of this relationship, we will explore urbanicity and sex as potential effect modifiers.

##### Statistical analysis

We will describe the greenspace and test score measures using the central tendency (mean, median) and variability statistics (standard deviation, quantiles). We will use a spatial multilevel mixed-effect model for multivariable analyses to explore the association between greenspace and test scores. The dependent variables, standardized PARCC scaled test scores, are expected to be continuous and normally distributed. The main independent variable is the proportion of greenspace within a walking-distance buffer of student residence and school. Our model will account for correlation among students within the same school using the random effect method. To account for spatial autocorrelation due to students living close to one another having similar test scores, we will use universal kriging and semivariogram to create the spatial covariance function for our model. We will also include covariates to adjust for confounding, as mentioned in the section above. We will evaluate confounding using the traditional method (including confounders with at least a 10% change in main beta coefficients when added to the model) and using our DAG informed minimally sufficient set of confounding factors. We expect that these covariates will be highly correlated; therefore we will explore the correlation matrix among these covariates and will control for the potential collinearity.

Since the outcome (scale test scores) cannot be compared across grades, we can only build a model for each grade. We will consider using one grade for each school level (elementary, middle, and high school). We will also build a model with a different grade, then use the data from a consecutive grade (within the same school level) to validate the model; this additional model validation will help strengthen our study results. All analyses will be conducted using the R statistical software environment and the main analysis will be implemented in the R-INLA and the lme4 packages.

To easily compare our results with previous studies, we will conduct additional analyses to (1) explore multiple circular buffer zones of 25m, 50m, and 100m, 250m, 500m, 1000, 2000m, and 4000m for residential and school, (2) use the average of only 1 year of NDVI data, and (3) explore combinations of NDVI data from different seasons. We will also report regression results from different DAG scenarios to account for the uncertainty of our DAGs due to limited evidence.

#### RESULTS

Table 1. Descriptive stats

Table 2. Regression model result

Figure 1. Distribution of NDVI values in the study area.

Figure 2. Distribution of NLCD categories in the study area.

Figure 3. Distribution of schools in the Adams district.

Figure 4. Close-up example of circular buffers and how greenspace measure would be calculated for (a) student residence and (b) school.

#### DISCUSSION

The strength of this aim is that the unit of analysis is at an individual level, not a school level, which allows incorporating SES variables, which are highly correlated with student test scores. The assessment of greenspace is thorough, using different types of data sources to represent different hypothesized mechanisms of greenspace effect on student test scores.

There are still limitations in our study approach. First, similar to aim 1, some of the potential confounders in our study will be measured at a census-tract level through linking student residential addresses to additional data sources. We expect residual confounding due to this use of census-tract level variables. Second, we did not assess the presence of lag time between the greenspace exposure and the academic achievement. We will not evaluate the different lag times since (1) we need to narrow the scope of the study, (2) previous literature did not have high variability on lag time, and (3) measurement error as we do not have student residential history and will have to assume the student had not moved from a different address to the address we have on file. However, we will discuss the potential impact of misclassification as part of the dissertation. Finally, for the greenspace assessment, we will exclude the “bluespace”–water surfaces–measurement by setting it as missing in our dataset. While this is the recommended practice, it is probable that (1) bluespace compensates for a lack of greenspace or (2) bluespace and greenspace are on two different causal pathways from the same ancestor to academic achievement, therefore accounting for bluespace might be important in understanding the effect of greenspace. However, literature on bluespace, particularly with academic achievement, is still nascent and does not provide clear evidence of its effects.

CHAPTER V

## DISCUSSION

Result summary

#### Strengths

#### Limitations

Aim 1

Heschong, Re-Analysis Report, Daylighting in Schools: showed that by separating grade did not show any difference patterns of the association between IEQ & academic achievement

Aim 2

Aim 3

Second, as vegetation indices assess the overall level of vegetation only and do not differentiate between structured (e.g., parks) and unstructured (e.g., street trees, backyards) vegetation, they are unable to assess the quality of greenspace. For example, an inaccessible abandoned lot overgrown with vegetation may give the same value as a widely used city park. Spatial/texture classification algorithms could help to solve this problem (Shoshany, 2002; Shoshany et al., 2012) but their use requires expert knowledge. Vegetation indices on their own are also poor at identifying vegetation types (trees, grass, and shrubs), but various machine learning algorithms and spectral and object classification approaches are emerging to solve this problem (Fan, 2013; Rodriguez-Galiano et al., 2012)

A third issue related to the use of these indices is that water surfaces (lakes, rivers, seas) receive a negative score (Weier and Herring, 2000). […] It is however probable that water surfaces have independent beneficial effects on health (e.g., Nutsford et al., 2016) or compensate for a lack of greenspace (de Vries et al., 2016). Studies are currently underway to explore this further, such as the European BlueHealth initiative (<http://www.ecehh.org/research-projects/bluehealth/>). If the research emphasis is only on greenspace, we recommend the removal of negative. values, especially in areas with large blue spaces, for which the greenspace exposure assignment will otherwise be substantially affected (i.e., artificially reduced; Ekkel and de Vries, 2017)

A large number of buffer distances have been applied in epidemiological studies, ranging from 30 m to 5000 m. There is also variability in how the buffers are calculated (circular buffers, as the “crow flies”, and more sophisticated measures that take into account distances along road networks). Furthermore, although buffers of certain sizes are often highly correlated (e.g., 100 m and 300 m), it is unknown what buffer sizes (and shapes, which are better able to take into account road networks and accessibility (Higgs et al., 2012)) are best suited for representing the different pathways within the mitigation, restoration and instoration domains. Conceivably, the relevant spatial scale might differ according to the specific pathway and health outcome within any of the domains. For greenspace reductions of traffic air pollution and noise, the relevant buffer size would be small (< 100 m), representing physical vegetation buffers (e.g. trees) along the roadways near residential locations. Similarly, for “viewsheds” around homes, small buffer distances might better represent restorative influences. Alternatively, larger buffers might better reflect potential influences of greenspace on recreational physical activity. It is also likely that the optimal buffer size may differ by population group as small children and senior citizens are more limited in their residential mobility than adults. Finally, in line with the uncertain geographic context problem, epidemiological findings could be affected by how the neighbourhood size and shape was defined before abstracting greenspace information (Kwan, 2012a, 2012b). As there is now nearly no available information on how to optimally define neighbourhoods for different outcomes, pathways and population groups, several buffer sizes and shapes should be tested, whenever possible.

#### Future studies

Instead, longitudinal, intervention and (quasi) experimental research designs should be employed whenever possible. Longitudinal cohort studies – in which participants can be traced through greener and less green residential neighbourhoods – have already shown that moves to greener or more natural places are associated with improved mental health and wellbeing (Alcock et al., 2015; van den Bosch et al., 2015; White et al., 2013). The addition of new spatial exposure measures and/or key questions on greenspace and behaviour involving greeenspace (e.g., “green” view from a window at home/work; amount of time spent outdoors in nearby greenspace conducting physical activity, socializing; ownership of a private garden; weekend and holiday travel to distant greenspace/leisure home; perceptions of restorative qualities of residential greenspace) to the many ongoing longitudinal studies is a realistic and cost-effective method of utilizing already existing resources for data collection. Researchers should also take advantage of natural experiments to capture the impact of a change in the quantity and quality of greenspace on health and the hypothesized pathways (e.g. Donovan et al., 2013; Giles-Corti et al.,2013; Astell-Burt, Feng and Kolt, 2016). Finally, small-scale experiments are still needed to advance the understanding of the affective, cognitive, physiological and social processes engaged in discrete encounters with greenspace which may over time lead to associations with different health outcomes.

CHAPTER VI

## SUMMARY

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# APPENDICES

### Appendix A

### Appendix B

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