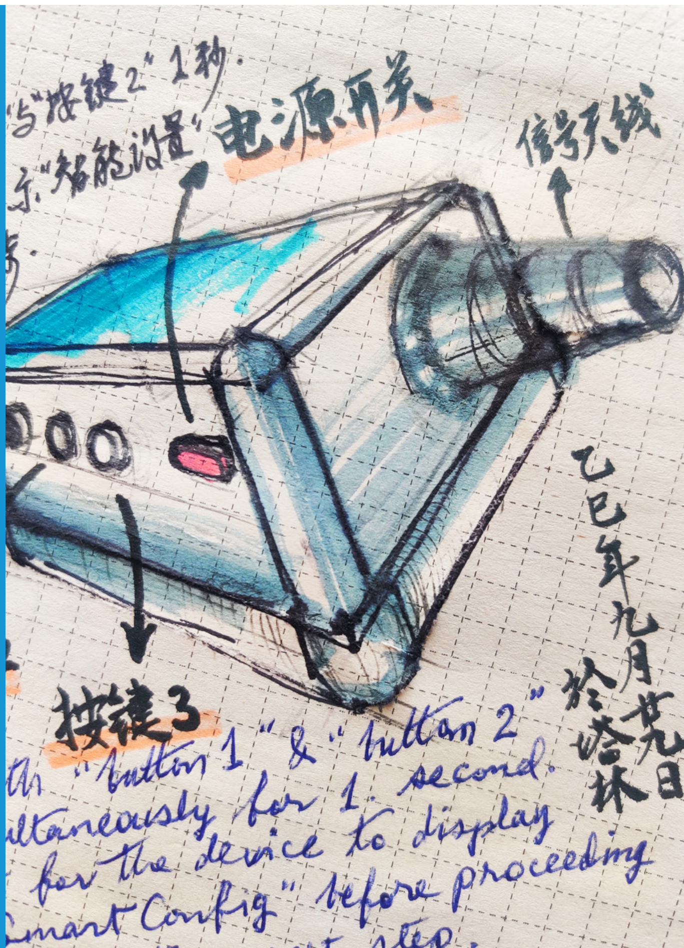
Robust universal framework for measuring sustainability on university campuses developing towards climate neutrality (PICSOU)

Qidi Jiang



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Robust universal framework for measuring sustainability on university campuses developing towards climate neutrality (PICSOU)

Qidi Jiang

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ABSTRACT

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Name of the doctoral thesis Robust universal framework for measuring sustainability on university campuses developing towards climate neutrality (PICSOU)

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Keywords sustainability, campus, indoor environmental quality, carbon footprint, transportation

This doctoral thesis develops and validates a robust universal framework, PICSOU (Performance Indicators for Core Sustainability Objectives of Universities), for measuring sustainability on university campuses developing towards climate neutrality. The research is motivated by the critical gap between the operational reality of campuses as complex systems and the limitations of existing assessment tools, which often lack empirically grounded, campus-scale performance indicators directly linked to carbon reduction goals.

Recognizing that building operations constitute a dominant, measurable component of a campus's environmental footprint, the thesis focuses on developing a core set of operational indicators for space utilization, indoor environmental quality, energy use, and carbon emissions. The work is based on longitudinal monitoring data and contextual information from multiple university buildings across different climatic zones, enabling the analysis of performance patterns under varying operational conditions.

A suite of analytical methods is developed to derive actionable indicators from raw data, including diagnostic analyses of indoor environmental quality, predictive modelling for embodied carbon, and multi-method workflows for commuting emissions. These methods are subjected to statistical validation to ensure robustness. The results demonstrate the sensitivity of performance indicators to measurement contexts and highlight how diagnostic, distribution-based metrics can reveal critical exceedance patterns often masked by aggregated scores.

The main contribution of the thesis is a transparent, empirically grounded, and operationally focused framework that translates campus-level climate neutrality objectives into a core set of measurable performance indicators. By clarifying the assumptions and providing validated methods for indicator application, the PICSOU framework enables universities to move beyond symbolic reporting towards evidence-based decision-making for measurable improvements in campus sustainability performance. The framework and its related findings are intended to complement, not replace, detailed building-specific analyses within the broader context of institutional climate action planning.

TALLINN UNIVERSITY OF TECHNOLOGY
DOCTORAL THESIS
38/2026

Robust universal framework for measuring sustainability on university campuses developing towards climate neutrality (PICSOU)

QIDI JIANG

TALLINN UNIVERSITY OF TECHNOLOGY
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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Qidi Jiang

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TALLINNA TEHNIKAÜLIKOOL
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Tugev universaalne raamistik ülikoolilinnakute jätkusuutlikkuse mõõtmiseks kliimaneutraalsuse suunas liikumisel (PICSOU)

QIDI JIANG

Lühikokkuvõte

Tugev universaalne raamistik ülikoolilinnakute jätkusuutlikkuse mõõtmiseks kliimaneutraalsuse suunas liikumisel (PICSOU)

See doktoritöö arendab ja valideerib robustse universaalse raamistiku PICSOU (ülikoolide jätkusuutlikkuse põhieesmärkide tulemusnäitajad) jätkusuutlikkuse mõõtmiseks ülikoolilinnakutes, mis arenevad kliimaneutraalsuse suunas. Uurimistöö ajendiks on kriitiline lõhe ülikoolilinnakute kui keerukate süsteemide toimimise reaalsuse ja olemasolevate hindamisvahendite piirangute vahel, millel sageli puuduvad empiiriliselt põhjendatud, ülikoolilinnaku tasandi tulemusnäitajad, mis on otseselt seotud süsinikuheite vähendamise eesmärkidega.

Tunnistades, et hoonete tegevus moodustab ülikoolilinnaku keskkonnajalajälje domineeriva ja mõõdetava komponendi, keskendub väitekiri ruumikasutuse, sisekeskkonna kvaliteedi, energiatarbimise ja süsinikdioksiidi heitkoguste põhiliste toimivusnäitajate väljatöötamisele. Töö põhineb pikisuunalistel seireandmetel ja kontekstuaalsel teabel mitmest ülikoolihoonest erinevates kliimavööndites, mis võimaldab analüüsida tulemuslikkuse mustreid erinevates töötingimustes.

Toorandmetest rakendatavate näitajate tuletamiseks töötatakse välja analüütiliste meetodite komplekt, sealhulgas sisekeskkonna kvaliteedi diagnostilised analüüsid, kehastunud süsiniku ennustav modelleerimine ja mitmemeetodilised töövood pendelrände heitkoguste jaoks. Need meetodid allutatakse statistilisele valideerimisele, et tagada usaldusväärsus. Tulemused näitavad tulemusnäitajate tundlikkust mõõtmiskontekstide suhtes ja toovad esile, kuidas diagnostilised, jaotuspõhised mõõdikud võivad paljastada kriitilisi ületamismustreid, mida koondtulemused sageli varjavad.

Dissertatsiooni peamine panus on läbipaistev, empiiriliselt põhjendatud ja operatiivselt keskendunud raamistik, mis teisendab ülikoolilinnaku tasandi kliimaneutraalsuse eesmärgid mõõdetavate tulemusnäitajate põhikogumiks. Eelduste selgitamise ja indikaatorite rakendamiseks valideeritud meetodite pakkumise abil võimaldab PICSOU raamistik ülikoolidel liikuda sümboolsest aruandlusest tõenduspõhise otsustusprotsessi poole, et saavutada ülikoolilinnaku jätkusuutlikkuse tulemuslikkuse mõõdetavaid parandusi. Raamistik ja sellega seotud järeldused on mõeldud täiendama, mitte asendama üksikasjalikke hoonepõhiseid analüüse institutsioonilise kliimameetmete planeerimise laiemas kontekstis.

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I would like to express my deepest and most sincere gratitude to my main supervisor, Professor Jarek Kurnitski, to whom I owe the greatest thanks. As a world-renowned scientist and a highly cited scholar in the field of building performance and energy efficiency, he has profoundly shaped both this doctoral work and my development as a researcher. His unique supervising style—grounded in trust, intellectual rigor, and independence—made me feel truly blessed *to be taught how to fish rather than simply being given the fish*. He consistently encouraged exploration, critical thinking, and ownership of ideas, while his unquenched curiosity for venturing into the unknown research landscape has been both inspiring and contagious. This spirit of exploration mirrors his excellence in the sport of kayaking, and it is a quality that defines his scientific leadership as much as his personal character. As Vice Rector for Research and Director of the Nearly Zero Energy Buildings (nZEB) Research Group at TalTech, he provided not only outstanding academic supervision but also a broader research vision that continuously pushed the boundaries of this work. Being based in the nZEB Research Group under his leadership has been both a privilege and a formative experience.

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The cross-climate validation of the PICSOU framework's IEQ indicators would not have been possible without the close cooperation of consortium partners in China. I would like to thank colleagues from Chengdu University of Technology and Southwest Jiaotong University for their collaboration, as well as the technical support team at the project site at Chengdu Jincheng College. Their openness, professionalism, and sustained engagement made it possible to extend the research beyond a single climatic and operational context.

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Tallinn, 17 December 2025,

Qidi Jiang

Contents

List of Publications

This doctoral thesis is based on the following publications:

1. Jiang Q, Kurnitski J. Performance based core sustainability metrics for university campuses developing towards climate neutrality: A robust PICSOU framework, *Sustainable Cities and Society*, Vol. 97, pp. 104723, October 2023. https://doi.org/10.1016/j.scs.2023.104723

2. Jiang Q, Kurnitski J. Comprehensive workflow for documenting corporate commuting emissions: a university case study with two alternative approaches, in Proceedings of *ACESS 2023 – 2nd International Conference on Advanced Civil Engineering and Smart Structures*, Chengdu, China, 25-26 Nov 2023, pp. 68-77. https://doi.org/10.1007/978-981-97-1514-5_8

3. Xie Q, Jiang Q, Kurnitski J, Yang J, Lin Z, Ye S. Quantitative Carbon Emission Prediction Model to Limit Embodied Carbon from Major Building Materials in Multi-Story Buildings, *Sustainability*, Vol. 16, Iss. 13, pp. 5575, June 2024. https://doi.org/10.3390/su16135575

4. Jiang Q, Liu C, Wang C, Chen Z, Salonen H, Kurnitski J. Modularizing the PICSOU Framework: Subtropical Climate Adaptation and Validation of University Campus IEQ Benchmarking, in Proceedings of *ICoGB 2025 – 3rd International Conference on Green Building*, Xi'an, China, 25-27 Apr 2025, pp. 15-25. https://doi.org/10.1007/978-3-032-14648-9_2

5. Jiang Q, Liu C, Wang C, Chen Z, Salonen H, Kurnitski J. Parameter Optimization for Climate-Resilient IEQ Assessment: Validating Essential Metrics in the PICSOU Framework across Divergent Climate Zones, *Buildings*, Vol. 16, Iss. 2, pp. 283, January 2026. https://doi.org/10.3390/buildings16020283

Authors' Contribution

Publication 1: Performance based core sustainability metrics for university campuses developing towards climate neutrality: A robust PICSOU framework

The author of this thesis is the principal author of Publication 1 and was responsible for literature review, preparation of figures and tables, structuring the manuscript and writing of the manuscript under the supervision of Prof. Jarek Kurnitski, who proposed and co-developed the original concept of the article, and provided critical data and ideas for data processing and analysis.

Publication 2: Comprehensive workflow for documenting corporate commuting emissions: a university case study with two alternative approaches

The author of this thesis is the principal author of Publication 2 and was responsible for literature review, preparation of figures and tables, structuring the manuscript and writing of the manuscript under the supervision of Prof. Jarek Kurnitski, who proposed and co-developed the original concept of the article, and provided critical data.

Publication 3: Quantitative Carbon Emission Prediction Model to Limit Embodied Carbon from Major Building Materials in Multi-Story Buildings

The author of this thesis is the co-author of Publication 3 and contributed to validation, visualization, and review and editing of the manuscript, and handled the peer review process including revisions in response to reviewers' comments. Prof. Qimiao Xie is the principal author and was responsible for conceptualization, methodology, formal analysis, project administration, and writing of the original draft under the supervision of Prof. Jarek Kurnitski, who acquired funding and supervised the research. Jiahang Yang participated in data curation and validation, while Zihao Lin contributed to data curation and visualization. Shiqi Ye assisted in data curation.

Publication 4: Modularizing the PICSOU Framework: Subtropical Climate Adaptation and Validation of University Campus IEQ Benchmarking

The author of this thesis is the co-principal author of Publication 4 along with Cheng Liu and Chunjian Wang and led the conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing of the original draft, visualization, and project administration, with assistance from Zhiyang Chen in these tasks. Prof. Jarek Kurnitski supervised the research and contributed to conceptualization, validation, formal analysis, data curation, writing-review and editing, visualization, project administration, and funding acquisition. Prof. Heidi Salonen contributed to supervision.

Publication 5: Parameter Optimization for Climate-Resilient IEQ Assessment: Validating Essential Metrics in the PICSOU Framework across Divergent Climate Zones

The author of this thesis is the principal author of Publication 5 and led the conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing of the original draft, visualization, and project administration, with assistance from Zhiyang Chen, Cheng Liu and Chunjian Wang in these tasks. Prof. Jarek Kurnitski supervised the research and contributed to conceptualization, validation, formal analysis, data curation, writing-review and editing, visualization, project administration, and funding acquisition. Prof. Heidi Salonen contributed to supervision.

List of Abbreviations

ANOVA	Analysis of variance
BIM	Building Information Modeling
BREEAM	Building Research Establishment Environmental Assessment Method
CCE	Climate Change and Energy
CDJCC	Chengdu Jincheng College
CO_2	Carbon dioxide
CON	Construction research building on TalTech campus
DOF	Degrees of freedom
EPBD	Energy Performance of Buildings Directive
FMCW	Frequency-modulated continuous wave
GIS	Geographic Information System
HEI	Higher education institution
ICT	Information and communication technology
IEQ	Indoor environmental quality
IPCC	International Panel on Climate Change
KPI	Key performance indicator
LCA	Life cycle assessment
LEED	Leadership in Energy and Environmental Design
MAC	Marginal abatement cost
MAPE	Mean absolute percentage error
NAA	Net assignable area
NASA	Non-assignable area
NUA	Net usable area

$PM_{2.5}$	Particulate matter with aerodynamic diameter ≤ 2.5 μm
PICSOU	Performance Indicators for Core Sustainability Objectives of Universities
QCEPM	Quantitative Carbon Emission Prediction Model
SDG	Sustainable development goal
STARS	Sustainability Tracking, Assessment and Rating System
TAIL	Thermal environment, acoustic environment, indoor air, and luminous environment
TalTech	Tallinn University of Technology
UI GreenMetric	Universitas Indonesia GreenMetric World University Ranking
VIF	Variance Inflation Factor

List of Symbols

a Annual net cash flow, as defined in Equation 26

ACH Air change frequency measured in 1/h, as defined in Equation 23

B Base investment cost, as defined in Equation 26

$C(t)$ CO_2 concentration at a given timestamp, as defined in Equations 2, 3

E Total carbon emissions, as defined in Equations 35, 37

E_i Unit area annual energy saving from specific energy use type or carbon foot print from specific mode of commuting, as defined in Equations 27, 35

EF_i Carbon emission factor for specific commuting mode, as defined in Equation 36

f_i Emission factor from specific energy use type, as defined in Equation 27

H Relative humidity, as defined in Equation 6

I/O Indoor-outdoor PM2.5 ratio, as defined in Equation 39

IQR Interquartile range, as defined in Equations 11-13

L_{fence} Lower fence, as defined in Equations 12, 14

m Number of samples equal to or greater than the i-th observed value in a sorted ranking, as defined in Equation 4

M Masonry quantity, as defined in Equation 37

n Sample size, as defined in Equations 5-7, 15, 33, 40

N Total number of observations, as defined in Equation 4

O_i Occupancy Detection Contributor (a binary value, 0: unoccupied, 1: occupied), as defined in Equation 5

$O(t)$ Occupancy status (a binary value, 0: unoccupied, 1: occupied) at a given timestamp, as defined in Equation 3

P Probability/percentage, as defined in Equation 4

P_i Unit energy price from specific type of energy, as defined in Equation 24

P_T Temperature-related productivity, as defined in Equations 20, 22

P_V Ventilation-related productivity, as defined in Equations 20, 21

$Q_{1/2/3}$ First/second (median)/third quartile, as defined in Equations 8-13

R Rebar quantity, as defined in Equation 37

s Sample standard deviation, as defined in Equation 15

SL Sick leave prevalence, as defined in Equations 20, 23

t Time variable, as defined in Equations 2, 3

T Temperature, as defined in Equation 22

U_{fence} Upper fence, as defined in Equations 13, 14

x, x_i Observation/measurement value or independent variable, as defined in Equations 4, 7-10, 14, 28-33

X Independent variable vector, as defined in Equation 31

$\bar{X}$ Mean monitored IEQ value, as defined in Equations 6

$y, yi, \hat{y}i$ Dependent variable, as defined in Equations 28, 29, 30, 32, 40

Y Dependent variable vector, as defined in Equation 30

β, β_i Regression coefficient, as defined in Equations 28-30, 32-34

$\Delta C(t)$ Change in CO2 concentration at a given timestamp, as defined in Equations 2, 3

$\varepsilon, \varepsilon_i$ Random error, as defined in Equations 28-30, 32, 34,

λ_{season} Seasonal ventilation efficacy coefficient, as defined in Equation 38

σ Standard deviation, as defined in Equations 33, 34

Σ Summation operator, as used in Equations 5, 6, 24, 27, 33, 35, 40

1 Introduction

This chapter sets the context and motivation for the thesis. It first outlines why university campuses have become relevant testbeds for sustainability and climate neutrality, then reviews existing assessment approaches and their limitations in the higher-education context. On this basis, it formulates the research gap that motivates the development of the Performance Indicators for Core Sustainability Objectives of Universities (PICSOU) framework, defines the research questions and objectives, and clarifies the scope, delimitations and novelty of the study. The chapter concludes by summarizing the overall structure of the thesis and the role of the appended publications.

1.1 The imperative for sustainable university campuses

The accelerating impacts of climate change continue to expose vulnerabilities in global socio-economic systems, while recent geopolitical uncertainties have disrupted mitigation trajectories that were already insufficient to meet long-term climate targets [1]. Achieving a rapid reduction in greenhouse gas emissions therefore remains essential for stabilizing the climate. The building sector plays a central role in this effort, accounting for roughly 40% of global energy consumption and associated emissions from fossil-fuel-based heat and power production [2]. This is especially significant given that individuals spend nearly 90% of their time indoors [3], making the performance of built environments closely tied to environmental impact and human well-being.

University campuses sit at the intersection of these conditions. They function as complex estates that combine academic spaces, laboratories, residential facilities, sports infrastructure and public services. Their hybrid nature results in a combination of energy-intensive activities and data-rich operational environments [4]. At the same time, universities increasingly face expectations to contribute to societal decarbonization efforts by aligning institutional operations with the United Nations Sustainable Development Goals (SDGs). The Sustainable Development Report 2023 highlights persistent global gaps in meeting climate-related SDGs and underscores the need for more coherent, evidence-supported action across all societal sectors, including higher education [5].

Universities have responded through carbon-neutrality pledges, campus-scale mitigation planning and expanded sustainability reporting [6]. Case studies show that common mitigation strategies include building retrofits, renewable-energy deployment and mobility management [7]. These efforts illustrate the operational diversity and complexity of campus environments and raise questions about how campus operations are currently measured and reported. Within this context, campuses represent both a meaningful site of emissions reduction and a unique setting for understanding how built-environment performance can be steered towards long-term climate objectives.

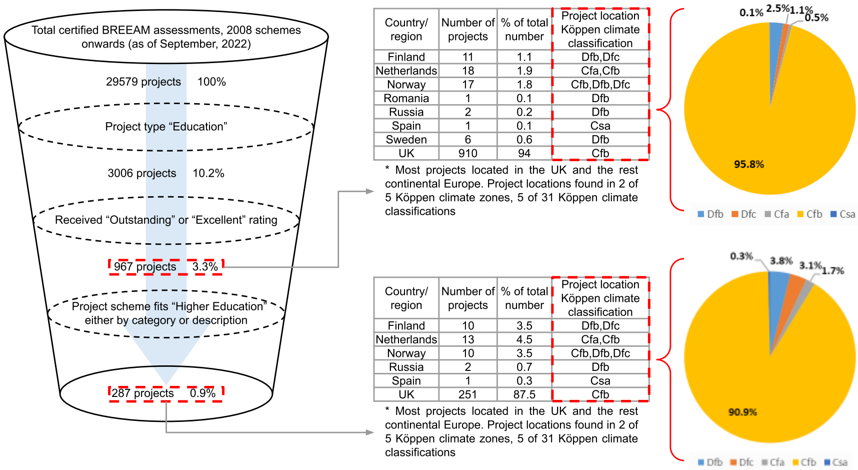
1.2 Review of existing sustainability assessment tools

Although many universities have their localized strategies for sustainability targets and diverse means to operationalize climate mitigation, the attempts to standardize the sustainable operation of higher education institution (HEI) into universal practice/technical requirements have largely relied on scorecard-based tools such as green building certification systems and institution-level sustainability assessment or ranking. Both types of tools have contributed to raising awareness of sustainability goals and climate issues by influencing institutional strategies while exhibiting structural limitations when applied to university campuses.

1.2.1 Green building standards

Green building rating systems such as Building Research Establishment Environmental Assessment Method (BREEAM) and Leadership in Energy and Environmental Design (LEED) were designed to evaluate the environmental performance of individual buildings or building clusters by focusing on different stages of a building's life cycle such as design and construction or operation and maintenance [8], [9]. Empirical studies have shown that their operational energy performance is variable, with numerous LEED-certified buildings failing to deliver consistent energy savings [10], [11]. Portfolio-level reviews of university campuses similarly show no systematic evidence that green-certified buildings achieve lower energy use than non-certified buildings across entire estates [12].

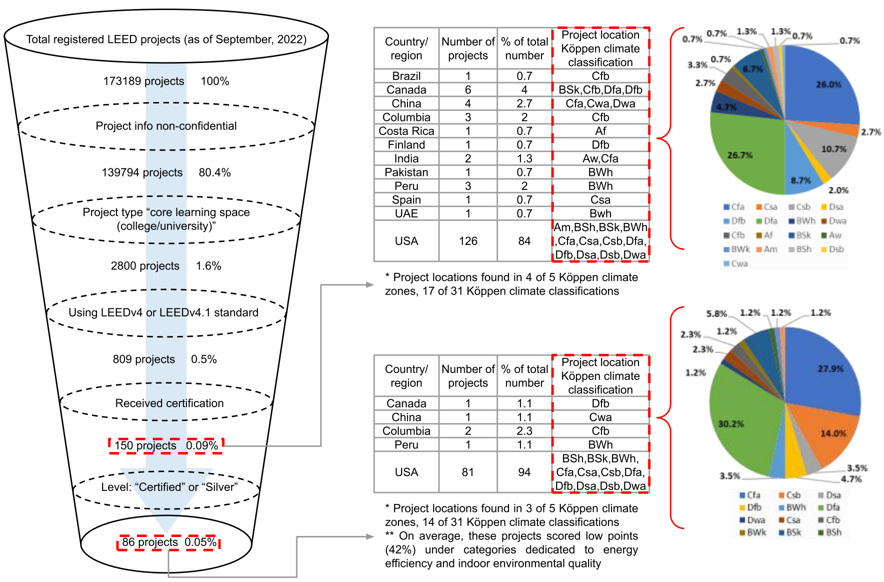
From a campus perspective, the limitations of green building standards are structural. Their scoring logic is building-centric, and certification outcomes allow projects to obtain ratings despite low performance in carbon-intensive categories such as energy and indoor environmental quality [10], [11]. Filtering global BREEAM and LEED project data further reveals that the number of university projects certified under the most recent versions is small relative to the full certification portfolio, geographically concentrated, and dominated by lower-tier certifications (see Figure 1 and Figure 2). These patterns indicate that although green building standards remain influential, they do not provide a universal, campus-scale sustainability assessment framework [13].



Country/ region	Number of projects	% of total number	Project location Köppen climate classification
Finland	11	1.1	Dfb,Dfc
Netherlands	18	1.9	Cfa,Cfb
Norway	17	1.8	Cfb,Dfb,Dfc
Romania	1	0.1	Dfb
Russia	2	0.2	Dfb
Spain	1	0.1	Csa
Sweden	6	0.6	Dfb
UK	910	94	Cfb

Country/ region	Number of projects	% of total number	Project location Köppen climate classification
Finland	10	3.5	Dfb,Dfc
Netherlands	13	4.5	Cfa,Cfb
Norway	10	3.5	Cfb,Dfb,Dfc
Russia	2	0.7	Dfb
Spain	1	0.3	Csa
UK	251	87.5	Cfb

Figure 1. Screening of BREEAM projects indicates limited distribution of locations and Köppen climate classifications (Publication 1)



Country/ region	Number of projects	% of total number	Project location Köppen climate classification
Brazil	1	0.7	Cfb
Canada	6	4	BSk,Cfb,Dfa,Dfb
China	4	2.7	Cfa,Cwa,Dwa
Columbia	3	2	Cfb
Costa Rica	1	0.7	Af
Finland	1	0.7	Dfb
India	2	1.3	Aw,Cfa
Pakistan	1	0.7	BWh
Peru	3	2	BWh
Spain	1	0.7	Csa
UAE	1	0.7	Bwh
USA	126	84	Am,BSh,BSk,BWh ,Cfa,Csa,Csb,Dfa, Dfb,Dsa,Dsb,Dwa

Country/ region	Number of projects	% of total number	Project location Köppen climate classification
Canada	1	1.1	Dfb
China	1	1.1	Cwa
Columbia	2	2.3	Cfb
Peru	1	1.1	BWh
USA	81	94	BSh,BSk,BWh, Cfa,Csa,Csb,Dfa, Dfb,Dsa,Dsb,Dwa

Figure 2. Screening of LEED projects indicates limited distribution of locations and Köppen climate classifications (Publication 1)

1.2.2 Sustainable campus rating and ranking systems

Parallel to building-centric approaches, universities increasingly engage with ranking-based assessments such as Universitas Indonesia GreenMetric World University Ranking (UI GreenMetric) [14], STARS [15] and other national or institutional frameworks. Early initiatives, including the Campus Sustainability Assessment Review Project, focused on indicator-based snapshots of operational performance [16]. More recent frameworks expanded coverage to include education, outreach, governance and research [17], [18].

Despite their breadth, campus sustainability rankings face methodological issues. Several indicators such as total floor area, budget or per-capita emissions can often be submitted without fully verifiable evidence [17], [19]. Reviews of assessment methods in higher education underline inconsistent indicator definitions, limited auditing and heavy reliance on self-reported data [20], [21].

Furthermore, recent studies highlight that while rankings promote visibility and institutional commitment, their indicator structures are not always aligned with the most material carbon and resource drivers on campuses [22]. University-wide carbon neutrality assessments often require bespoke methods that fall outside existing ranking frameworks [23]. Consequently, the literature converges on three diagnostics:

1. Inconsistent indicator definitions and scopes across assessment tools
2. Extensive dependence on self-reported data with lenient verification
3. Weak coupling between ranking indicators and campus operational data

These limitations collectively demonstrate why even some of the most widely applied sustainability tools remain insufficient as universal frameworks for measuring and improving campus-scale sustainability performance.

1.3 Research gap and need for a universal framework

The findings reviewed in Section 1.2 indicate that current approaches to campus sustainability assessment lack a consistent basis for evaluating operational performance. Although numerous tools exist, their structures differ markedly in terms of indicator definitions, data requirements and reporting procedures. As a result, it is difficult to determine whether variations in assessment outcomes reflect real performance differences or simply differences in assessment methods.

Recognizing the need for a tractable and evidence-based approach, this thesis focuses on operational performance domains—energy use, carbon emissions, indoor environmental conditions, and commuting patterns—where data is commonly measurable and impacts are directly linked to campus resource flows and climate goals. Consequently, the indicators developed for a universal framework are chosen to be applicable across different institutional and climatic contexts and to focus on aspects of performance with direct relevance to these measurable operational outcomes. This scope defines the framework's purpose as an operational diagnostic tool, acknowledging it does not encompass all facets of campus sustainability.

The absence of a set of measurable operational indicators constitutes the central research gap addressed in this thesis. Existing assessment tools provide partial perspectives, but none offers a minimum collection of indicators that can be used reliably to interpret sustainability performance across different university campuses. Addressing this gap requires a systematic examination of which indicators matter most, how they can be measured consistently and how they behave when applied to campuses within varying local contexts. It is with the above intention that the PICSOU framework was first proposed/identified and further developed/validated throughout later studies discussed in this thesis.

1.4 Research questions and objectives

The evidence reviewed in Sections 1.1–1.3 indicates that the current landscape of sustainability assessment tools for university campuses is characterized by methodological inconsistencies, varying indicator relevance and limited operational alignment. These observations motivate a focused set of research questions that establish the analytical boundaries of this thesis. These questions originate from the conceptual critiques outlined in Publication 1, and they remain sufficiently broad to encompass the methodological and empirical findings presented across Publications 2–5:

1. What characterizes an effective, practical alternative assessment framework for campus sustainability that does not rely on composite scoring or ranking logic?
2. What are the functional requirements and demonstrated outcomes of a campus sustainability assessment framework when designed and applied primarily as a decision-support tool for managing core sustainability objectives of campus operation?

These two questions frame the central inquiry of the thesis and guide the analytical progression from understanding the limitations of existing assessment to developing an empirical alternative for operational applications.

In line with these questions, the thesis pursues three objectives originally formulated in Publication 1 and further investigated through Publication 2 to Publication 5:

1. To identify a practical approach for assessing campus sustainability using indicators that reflect measurable operational performance and limit dependence on incompletely verifiable inputs.
2. To analyze the trade-offs associated with different assessment methods and determine how these trade-offs affect the accuracy and usefulness of assessment outcomes.
3. To develop evidence-supported recommendations for improving campus sustainability assessment practices, with emphasis on indicator relevance, data requirements and applicability across institutions.

These objectives define the analytical tasks undertaken in the thesis and outline the criteria - against which existing/alternative assessment approaches are examined/validated.

1.5 Scope and delimitations of the thesis

This thesis examines how the sustainability performance of university campuses can be assessed using indicators that reflect measurable aspects of campus operation. The focus is on variables that influence energy use, emissions, indoor environmental conditions and commuting patterns, along with built-environment characteristics that can be evaluated consistently across institutions.

The scope of the thesis is limited to assessment practices applied at the campus scale. Broader policy frameworks, city-level climate strategies and general sustainability auditing approaches are referenced only where necessary to contextualize campus assessment, but they are not analyzed in detail. Assessment tools designed specifically for commercial buildings or single-use facilities fall outside the main scope unless their methods provide transferable elements relevant to university campuses.

The empirical components draw on case studies from HEIs in different climatic regions. These cases are used to examine how selected indicators behave, how consistently they can be measured and how they contribute to understanding campus-level performance. The thesis does not aim to produce a global survey of campus performance or to rate individual institutions. Instead, it focuses on identifying indicator patterns and measurement properties that support consistent interpretation.

The analysis is further limited to data types commonly available at most universities. Highly specialized monitoring setups, experimental measurement campaigns and institution-specific reporting practices are not included unless they demonstrate methodological transferability. The aim is to identify applicable approaches without requiring institution-specific data systems.

Together, these delimitations define the boundaries within which the thesis evaluates how campus sustainability performance can be interpreted and improved using a concise set of measurable indicators (see Table 1).

Table 1. Scope and delimitations of the thesis

Scope/delimitation category	Included	Excluded
Scale of analysis	Campus-level sustainability assessment	National-scale policy evaluation; city-wide climate strategy analysis
Type of indicators	Measurable variables related to energy use, emissions, indoor environmental quality, commuting patterns and built-environment characteristics	Broad, theme-based indicators without operational measurement basis
Types of assessment tools	Tools relevant to university campuses; methods with transferable elements	Tools designed exclusively for commercial buildings or single-use facilities
Empirical components	Case studies from universities in different climatic regions	Global performance surveys; institutional ranking; competitive benchmarking
Data requirements	Commonly available campus data; standard operational measurements	Specialized monitoring setups; institution-specific or experimental data systems unless they demonstrate methodological transferability
Intended analytical output	Approaches suitable for universities without unique data systems	Approaches requiring bespoke or institution-specific data infrastructure
Overall purpose	Interpreting and improving campus sustainability performance using a concise set of measurable indicators	Comparing or ranking campuses; producing league tables or score-based evaluations

1.6 Novelty of study

The contributions outlined in this section define a methodological position that sits between general, score-based sustainability assessment tools and institution-specific reporting practices. Existing approaches either provide broad classifications with limited relevance to actual campus conditions or rely on local reporting formats that restrict their interpretive value. The indicator logic developed in this thesis occupies the intermediate space between these two categories by linking measurable conditions with institution-level sustainability interpretation as illustrated in Figure 3.

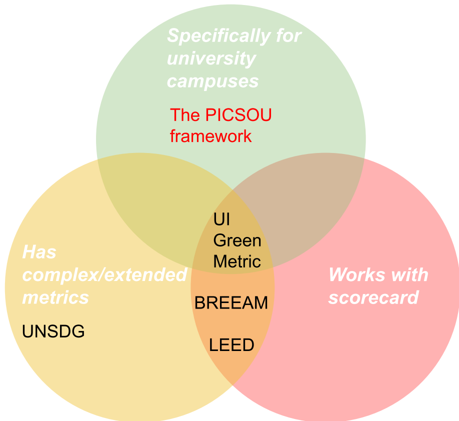


Figure 3. The relation between the PICSOU framework and existing tools (Publication 1)

The novelty of this study is structured into three theoretical contributions (T1-T3) and three practical contributions (P1-P3), their alignment with the five publications is summarized in Table 2.

The first theoretical contribution (T1: operational framing) defines an operational interpretation of campus sustainability performance based on a concise set of measurable variables. Existing frameworks rely on thematic scorecards or composite indices that obscure the operational conditions driving environmental impact.

The second contribution (T2: diagnostic logic) introduces a non-comparative orientation for interpreting sustainability performance. Rather than positioning institutions through rankings or benchmarking, the thesis shows how performance can be interpreted internally based on operational conditions and improvement potential.

The third contribution (T3: dominant drivers) demonstrates that a limited subset of operational indicators captures the main drivers of campus-level sustainability performance. The thesis provides a structured justification for relying on these variables when interpreting performance patterns or prioritizing interventions.

The first practical contribution (P1: applicable indicators) is the development of an indicator-based approach that institutions can apply using commonly available operational data.

The second contribution (P2: contextual behavior) demonstrates how selected indicators behave across different campus and climatic contexts and shows how this behavior can be used to identify performance gaps and improvement priorities.

The third contribution (P3: replicable interpretation) is the formulation of an interpretive structure that does not rely on specialized monitoring systems or institution-specific infrastructures. This allows universities to assess operational performance using data that are readily available.

Table 2. Contribution-publication matrix

Theoretical (T)/ Practical (P) contribution	Contribution focus	Addressed in Publication 1	2	3	4	5
T1: Operational framing	Establishes an operational interpretation of campus sustainability based on a concise set of measurable variables.	✓	✓	✓	✓	✓
T2: Diagnostic logic	Provides a conceptual alternative to score-based and ranking-oriented frameworks by introducing a diagnostic, non-comparative logic for measuring sustainability performance.	✓				
T3: Dominant drivers	Explains why a limited subset of operational indicators captures the dominant drivers of campus-level sustainability performance.	✓		✓		
P1: Applicable indicators	Develops an indicator-based approach that institutions can apply using commonly available operational data.	✓	✓	✓		
P2: Contextual behavior	Demonstrates indicator behavior across different campus and climatic contexts to identify performance gaps and improvement priorities.	✓	✓	✓	✓	✓
P3: Replicable interpretation	Provides a replicable interpretive structure that does not require specialized monitoring systems or unique data infrastructures.	✓	✓	✓		

1.7 Thesis structure and publication synopses

The thesis is organized to follow the analytical progression of the PICSOU framework from conceptual formulation through category-based empirical validation to cross-category synthesis. The appended publications are embedded within this chapter structure according to their methodological and empirical roles rather than presented as standalone case narratives.

Chapter 2 (Methods) defines the overall research strategy, with Section 2.1 presenting the methodological architecture that supports the formulation of PICSOU as a minimum operational indicator set and its subsequent validation across multiple campuses, data sources and climatic conditions. Section 2.2 documents methods for space efficiency and learning environments, including indicators for room utilization and the ratio of parking provision. Section 2.3 details methods for indoor environmental quality (IEQ) assessment, covering campus descriptions and reference thresholds, occupancy detection using Frequency Modulated Continuous Wave (FMCW) radar and carbon dioxide-proxy inference, temporal and distribution-based IEQ analyses, statistical validation of diagnostic parameters, and the economic valuation of IEQ improvements. Section 2.4 addresses climate change and energy (CCE) methods, defining approaches for operational carbon footprint assessment and introducing the Quantitative Carbon Emission Prediction Model's (QCEPM) regression analysis results for estimating embodied carbon footprint based on material inventories. Section 2.5 presents transportation methods, including PICSOU commuting indicators, multi-source data acquisition from survey and information and communication technology (ICT) platforms, and commuting carbon footprint calculation with sensitivity analysis.

Chapter 3 (Results) compiles findings by PICSOU category. Section 3.1 reports space-use and parking efficiency results based primarily on the Tallinn University of Technology (TalTech) case study developed in Publication 1. Section 3.3 consolidates IEQ results from Publications 1, 4 and 5, integrating TalTech baseline performance, sensor-based measurements at Chengdu Jincheng College (CDJCC), TalTech diagnostic analyses, cross-campus comparison against PICSOU IEQ benchmark thresholds and monetized IEQ improvement outcomes originally quantified in Publication 1. Section 3.4 presents CCE results, combining the operational campus carbon footprint reported in Publication 1 with the embodied building carbon footprint derived from QCEPM modelling in Publication 3. Section 3.5 reports transportation results from Publications 1 and 2, including survey-based and ICT-based commuting carbon footprint estimates, workflow comparisons, and mode-specific contributions to total commuting carbon footprint.

Chapter 4 (Discussion) interprets the category-based results in terms of robustness, applicability and institutional relevance. Section 4.1 examines space-use and parking efficiency patterns and implications for campus facility management. Section 4.2 discusses IEQ performance differences between campuses, the reliability of diagnostic parameters validated using statistical inference methods, compliance with PICSOU IEQ thresholds, and the economic significance of IEQ co-benefits for retrofit decision-making. Section 4.3 reflects on operational and embodied carbon footprint patterns and their relative contributions at campus scale. Section 4.4 interprets transportation findings by contrasting survey-based and ICT-based commuting carbon footprint assessment workflows and evaluating implications for mobility planning and policy. Section 4.5 synthesizes intra and cross-category interactions and provides an integrated assessment of the PICSOU framework as a decision-support tool.

Chapter 5 (Conclusions) provides the thesis-level synthesis and reflective discussion. Section 5.1 consolidates the literature-grounded justification for the composition of the PICSOU framework, with dedicated subsections (5.1 to 5.4) for each of its four core operational categories (space efficiency & learning environment, IEQ, CCE, and transportation). These sections integrate foundational academic literature, standards, and principles with the thesis's empirical findings to solidify the theoretical basis for the framework's indicator selection. Section 5.5 presents the integrated answers to the overarching research questions formulated in Section 1.4, synthesizing evidence across all PICSOU categories. Section 5.6 assesses the degree to which the three primary research objectives have been achieved. Section 5.7 details the principal limitations of the study, distinguishing between methodological and contextual constraints and broader conceptual reflections on the assessment paradigm. Finally, Section 5.8 outlines coherent directions for future research, including the further development and application of the PICSOU framework, expanded multi-climate validation, and policy-oriented implementations.

2 Methods

This chapter presents the methodological foundations of the thesis. It introduces the overarching research design and documents the category-specific methods applied to quantify sustainability performance on university campuses in alignment with the PICSOU framework. The chapter is structured in the same sequential order as the sustainability categories under the PICSOU framework that have been studied in depth in this thesis: space efficiency and learning environments, IEQ, CCE, and transportation. Within each category, procedures for data acquisition, processing, and analysis/validation are described to establish a consistent analytical basis for the results presented in Chapter 3.

2.1 Research methodology and architecture

The methodological architecture of this research is designed to develop, test, and validate the PICSOU framework as a minimum set of measurable indicators for campus sustainability assessment across heterogeneous institutional and climatic contexts. The research strategy follows a sequential logic: (i) conceptual definition of indicator categories and metrics, (ii) acquisition of category-specific empirical data, and (iii) application of analytical and statistical validation procedures.

The initial stage is documented in Publication 1, which establishes the PICSOU categorical structure and defines operational key performance indicators (KPI) for space efficiency, IEQ, CCE, and transportation. Baseline datasets from the TalTech campus are used to test indicator feasibility and internal coherence at institutional scale. This stage provides the methodological reference against which subsequent category-specific investigations are aligned.

The second stage focuses on data acquisition and category-level analytical expansion. Each sustainability domain is addressed using methods tailored to its measurement characteristics. Space-use assessments apply room utilization metrics and parking space ratios derived from spatial mapping and usage scheduling records (Publication 1). Transportation assessment develops two parallel workflows: a conventional survey-based commuting analysis and an ICT-based approach employing integrated Telia Crowd Insight and Fyma datasets, allowing direct evaluation of methodological sensitivity and uncertainty (Publication 2). Embodied carbon footprint modelling is conducted using QCEPM, a regression-based framework linking building material quantities to carbon footprint estimations for multi-story buildings (Publication 3). IEQ assessments incorporate multi-sensor monitoring campaigns implemented at TalTech and CDJCC, combining direct environmental measurements with occupancy detection techniques adapted to site-specific data availability (Publications 4 and 5).

The third stage applies statistical validation and comparative inference to strengthen cross-context robustness. Within the IEQ domain, distribution-based analyses, diagnostic parameter extraction, and t-distribution-based inference are applied to verify the stability of climate-resilient performance parameters under limited sample conditions (Publication 5). Transportation workflows are evaluated by direct comparison between survey-based and ICT-based commuting carbon-footprint estimates to assess consistency and systematic bias (Publication 2). The QCEPM framework is validated by comparison between model predictions and case-study material inventories (Publication 3). These validation procedures collectively ensure that observed category-level outcomes are not products of site-specific sampling designs or data heterogeneity.

The selection of the four core assessment domains, which correspond to the first four of the six categories of the PICSOU framework: space efficiency and learning environment, IEQ, CCE, and transportation, is deliberate. These domains represent primary operational areas where campus activities directly intersect with resource consumption, carbon emissions, and occupant wellbeing. They were chosen because (a) they are universally relevant to university campuses regardless of location or size, (b) their performance can be quantified using high-resolution, empirical data (e.g., sensor measurements, energy meters, space-use records), and (c) they align with the measurable operational targets commonly found in campus climate action plans. This focus enables the framework to serve as a diagnostic tool for operational performance, rather than attempting a comprehensive assessment of all sustainability themes.

2.2 Methods for space efficiency and learning environment

2.2.1 Space efficiency indicators

Space efficiency assessment within the PICSOU framework quantifies to which extent teaching and learning spaces are used relative to their assigned operating capacity. The methodological formulation of this indicator set is based on the utilization practices adopted in Publication 1, which in turn follow established university space-planning guidelines [24], [25], [26], [27], [28].

The primary indicator applied is the room utilization rate, defined in Publication 1, in line with the schedule-based utilization definitions used by [26] as expressed in Equation (1).

$$Utilization = Frequency * Occupancy \tag{1}$$

where occupancy is derived from institutional timetables and booking records, while the available operating time is determined from the standard academic week and designated teaching hours in each building. This formulation follows the established convention where utilization is derived from the joint effect of frequency of booking and occupancy relative to room capacity [25], [26], [28].

Utilization metrics are interpreted together with spatial allocation data. Floor-area inventories are combined with timetable-based utilization results to construct joint temporal–spatial indicators that link occupancy intensity with per-room and per-building space provision (Publication 1). This combination allows space-efficiency assessment to reflect not only how often rooms are booked, but also how much floor area is dedicated to different types of academic and support functions.

Room-level utilization values are aggregated into functional-category means to reduce the influence of atypical scheduling patterns in individual rooms. In Publication 1, this aggregation is carried out for main space types such as classrooms, laboratories, offices and shared learning areas, enabling campus-scale assessment while retaining differentiation between core functional categories (Publication 1). The resulting category-level indicators form the methodological basis for the space-efficiency component of the PICSOU framework and provide input metrics for later synthesis in Chapter 3 of the thesis.

2.2.2 Ratio of parking space

Parking space efficiency is included as a key indicator within the space-use domain because it serves as a proxy for both land-use efficiency and transportation-related carbon impacts. Inefficient parking provision can encourage private vehicle use, directly affecting Scope 3 emissions, while also representing a significant consumption of campus land that could otherwise avoid being used or repurposed for alternative uses.

The parking-space indicator is defined as a population-normalized parking provision ratio, calculated as the total number of designated on-campus parking spaces divided by the university population, where university population is defined as the sum of all enrolled students and employed academic and administrative staff present onsite during the assessment year (Publication 1). Parking-space counts are compiled from institutional estate inventories and campus infrastructure records, while population figures are obtained from official annual enrolment and personnel statistics published by the respective university administrations for the corresponding assessment year (Publication 1).

The benchmark procedure applied follows the approach described in Publication 1, drawing on established higher-education parking provision standards including the LEED v4 BD+C Reference Guide [29], Institute of Transportation Engineers guidance [30], and the local regulation [31]; compliant parking provision levels are estimated using both international guideline-based calculations and applicable regulatory limits, with the smaller of the two values adopted as the target threshold for the PICSOU parking indicator (see Figure 4). Empirical campus-specific parking ratios are reported separately in the results chapter.

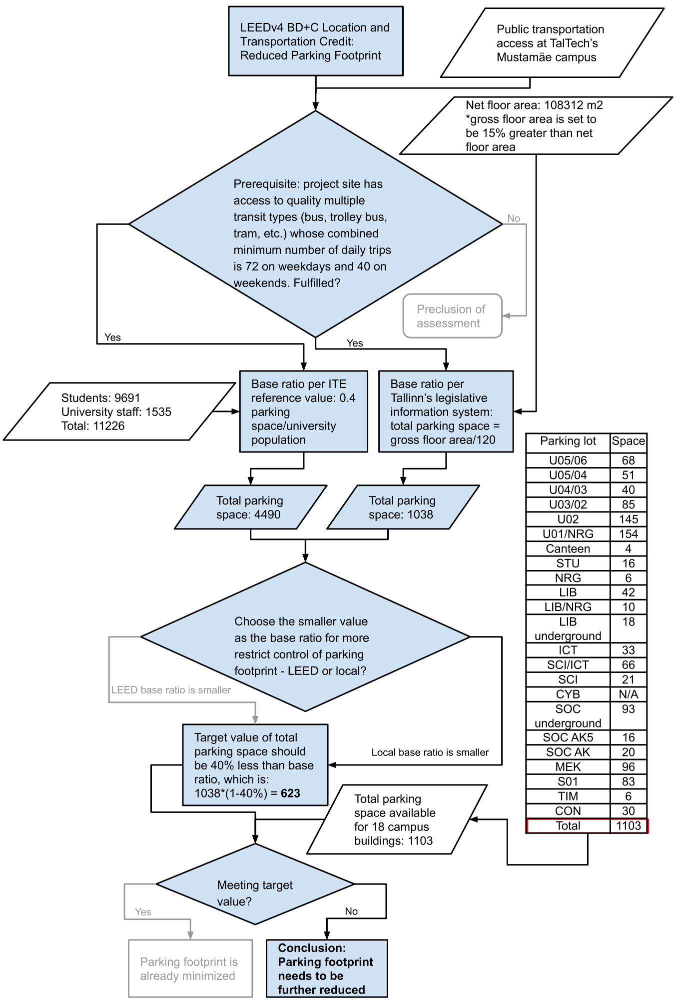


Figure 4. Workflow for deciding parking space's target value. Major steps followed in this flowchart are highlighted using color-filled shapes.

2.3 Methods for IEQ

2.3.1 Study sites, space types, and IEQ benchmarks

We conducted IEQ field measurements on two distinct university campuses: CDJCC in Chengdu, China, located in a subtropical monsoon climate (Cwa in Köppen climate classification,) featured by hot rainy summers, mild, damp winters with persistently high humidity. TalTech in Tallinn, Estonia, located in a temperate climate (Dfb in Köppen climate classification) which is mild and humid year-round, with evenly distributed precipitation and significant differences in daylight hours between seasons thanks to its high latitude. The spatial contexts and sensor deployment overview on both campuses are illustrated in Figure 5 and Figure 6.

Figure 5. Map of CDJCC with sensor locations

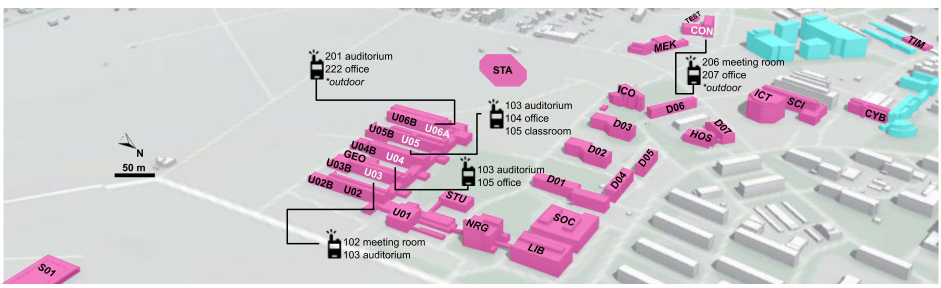


Figure 6. Map of TalTech with sensor locations

At CDJCC, during the 2024 autumn semester, we deployed sensors across 6 dormitories, 2 offices, 4 classrooms, and 1 outdoor location. During the spring semester, we adopted a mostly identical sensor deployment scheme (only changed 2 office locations during the 2025 spring semester due to limited accessibility) with 1 additional outdoor location for enhanced verification of outdoor air quality. Illustration of sensor location within each space type is shown in Figure 7.

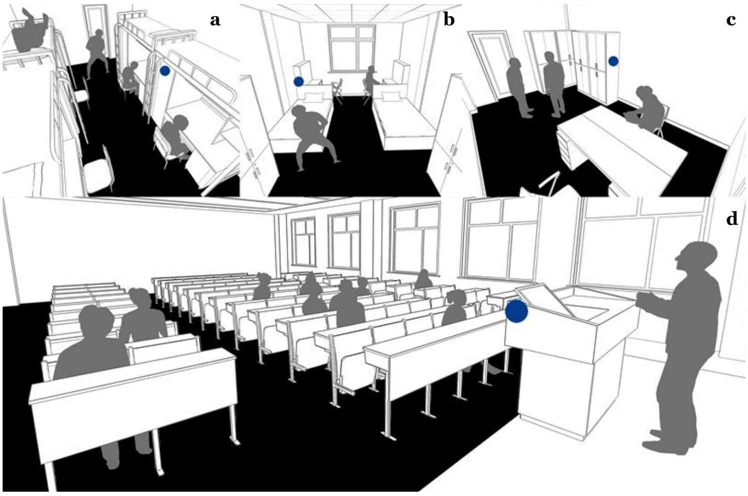


Figure 7. CDJCC sensor location in typical space types: (a) 4-person dormitory, (b) 2-person dormitory, (c) office, (d) classroom

From TalTech campus' widespread network of permanently installed sensors, we compiled a dataset from 13 sensors—7 classrooms/auditoriums/meeting rooms, 4 offices, and 2 outdoor locations. Illustration of sensor location within each space type is shown in Figure 8.

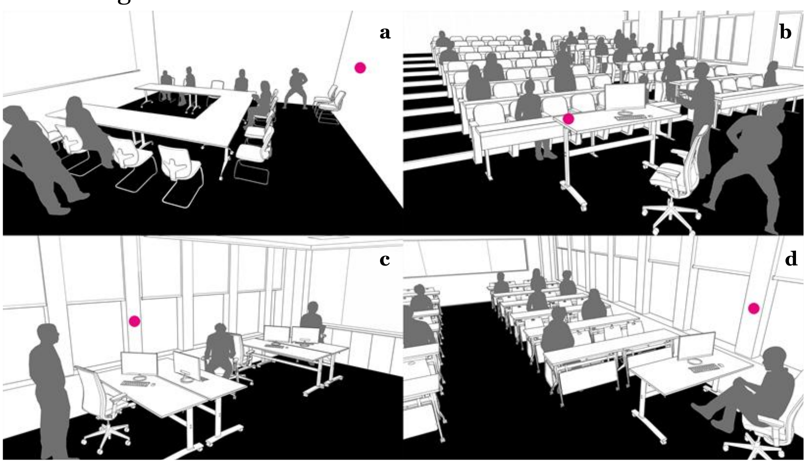


Figure 8. TalTech sensor location in typical space types: (a) meeting room, (b) auditorium, (c) office, (d) classroom

Across both campuses, default IEQ monitoring focused on four parameters: carbon dioxide concentration (CO_2), fine particulate matter with aerodynamic diameter ≤ 2.5 μm ($PM_{2.5}$), air temperature (T) and relative humidity (RH). At CDJCC campus, real-time occupancy status was also monitored in parallel to the default IEQ parameters by the integrated motion sensing module within the same sensor (elaborated in later sections of this chapter).

IEQ reference values used to interpret measured indicator levels are consolidated across both campuses. These threshold values derive from the national, European, and international standards [32], [33], [34] were adopted without modification as the uniform benchmarks (see Table 3).

Table 3. Critical IEQ reference values

Semester	**Issuer**	**Standard**	**CO_2, ppm**	**$PM_{2.5}$, μg/m³**	**Temperature, °C**	**Relative Humidity, %**
Spring	China	GB/T 18883-2022	**1000**	**75** (24h avg.)	Summer:22-**28**	Summer:40-80
		T/ASC 02-2021	1000	35 (Max.5 days/1y) or 15(1y avg.)	N/A	N/A
	EU	EN 16798-1:2019	**I: 950** **II: 1200** **III: 1750** **IV: 1750**	N/A	**I**: 23,5 - **25,5** **II**: 23 - **26** **III**: 22 - **27** **IV**: 21 – **28**	N/A
	WHO	AQG 2021	N/A	AQG: **5** **Interim** 4/3/2/**1**: 10/15/25/**35**	N/A	N/A
Autumn	China	GB/T 18883-2022	**1000**	**75** (24h avg.)	Winter:**16**-24	Winter:30-60
		GB 50325-2020	1000	N/A	N/A	N/A
		T/ASC 02-2021	1000	35 (Max.5 days/1y) or 15(1y avg.)	N/A	N/A
	EU	EN 16798-1:2019	**I: 950** **II: 1200** **III: 1750** **IV: 1750**	N/A	**I**: **21** - 23 **II**: **20** - 24 **III**: 19/**18**-25 **IV**: **17**-25	N/A
	WHO	AQG 2021	N/A	AQG: 5 Interim 4/3/2/**1**: 10/15/25/**35**	N/A	N/A

2.3.2 Sensor specifications

On the CDJCC campus, we customized our sensor units by integrating dedicated modules for IEQ measurement and human presence detection, all sensors shared identical parameters and specifications (see
Table **4**).

Table 4. CDJCC sensor specifications

Device	Module	Accuracy	Resolution	Range
	CO_2	≤ ±40 ppm, ±3% of reading	1 ppm	0-9999 ppm
	$PM_{2.5}$	±10 μg @ 0-100 μg/m³ ±10% @ 101-500 μg/m³	1 μg/m³	0-999 μg/m³
	Temperature	≤ ±0.2°C	0.1 °C	0-65°C
	Relative Humidity	≤ ±3%	0.10%	0-99%
	Occupancy	N/A	N/A	±60 degrees, 6 meters

On the TalTech campus, IEQ monitoring is outsourced to specialized industrial partner who manages a network of permanently installed sensors on the campus. All sensors shared identical parameters and specifications (see Table 5).

Table 5. TalTech sensor specifications

Device	Module	Accuracy	Resolution	Range
	CO_2	≤ ±40 ppm, ±3% of reading	1 ppm	10-40000 ppm
	$PM_{2.5}$	±10 μg @ 0-100 μg/m³ ±10% @ 101-1000 μg/m³	1 μg/m3	0-1000 μg/m³
	Temperature	≤ ±0.8°C	0.1 °C	-10 - 60°C
	Relative Humidity	≤ ±6%	0.10%	0-100%

2.3.3 Monitoring protocols

In this study, we defined the monitoring periods and sampling intervals to align with the academic calendars and operational characteristics of the respective campuses, ensuring our collected data was representative of typical use conditions.

On the CDJCC campus, we conducted monitoring over two discrete 15-calendar-day periods during the autumn and spring semesters to capture seasonal variations using temporarily installed custom-built sensors. We scheduled the autumn semester monitoring from 17 December to 31 December 2024, and the spring semester monitoring from 9 May to 23 May 2025. We sampled data from all parameters, including IEQ indicators and occupancy status, at a high frequency of 1-minute intervals to capture the dynamic, short-term fluctuations.

For TalTech, we leveraged a network of permanently installed IEQ sensors on campus managed by an industrial partner who set the sampling frequency at a 10-minute interval. To compensate for larger sampling intervals, we conducted monitoring over more extended periods that coincided with the core teaching semesters. We defined the monitoring period for the autumn semester as 22 September to 20 December 2024, and for the spring semester as 2 May to 21 June 2025, intentionally omitting the extended heating season between January and April (Publication 5).

2.3.4 Occupancy detection and inference

Accurate determination of occupancy was fundamental to our IEQ analysis, as it allowed us to filter data and assess environmental conditions specifically during occupied periods, which is critical for evaluating the performance of the spaces in use. The methods for occupancy detection differed between the two campuses, reflecting the distinct sensing technologies and data availability.

For the CDJCC campus, our custom-built sensor units with an integrated FMCW radar module were able to detect human presence within a range of ±60 degrees and up to 6 meters. This provided a direct, privacy-preserving method for real-time occupancy detection. The module generated a binary occupancy status (presence detected/undetected) at one-minute intervals, synchronized with the IEQ parameter measurements. This direct detection method allowed us to precisely identify occupied periods for subsequent analysis without relying on proxy indicators.

For the TalTech campus, where the permanently installed sensors lacked dedicated occupancy detection modules, we inferred occupancy status indirectly from the indoor CO_2 concentration data. The inference was based on the principle that human respiration is the primary source of CO_2 concentration in occupied indoor spaces. We applied a rule-based algorithm defined by the following Equations.

The change in CO_2 concentration between consecutive time steps is given by:

$$\Delta C(t) = C(t) - C(t-1) \tag{2}$$

The occupancy status $O(t)$ at time t was then determined by:

$$O(t) = \begin{cases} 1, & if\, \Delta C(t) > 0 \text{ and } C(t) > 550 \\ 0, & otherwise \end{cases} \quad (3)$$

in which, a space is classified as occupied ($O(t) = 1$) only if the CO_2 concentration is both increasing ($\Delta C(t) > 0$) and exceeds an absolute threshold of 550 ppm ($C(t) > 550$). This method provided a practical approach to estimate occupancy periods using the available data stream, acknowledging that it may be less responsive to rapid changes in occupancy compared to direct detection (Publication 5).

In both cases, the resulting occupancy data (whether directly detected or inferred) was used to filter the continuous IEQ time-series data. This enabled us to perform a targeted analysis focused exclusively on periods when spaces were in use, which is essential for a meaningful assessment of IEQ performance relative to the benchmarks established in Table 3.

2.3.5 Temporal IEQ analysis

The temporal analysis of IEQ data characterizes how parameters vary over time, providing insights into the frequency, duration, and magnitude of exceedances beyond static thresholds. This analysis employs duration curves to visualize the distribution of IEQ indicators across the monitoring period.

We conduct the temporal analysis using duration curves, also referred to as duration-exceedance curves. This method involves sorting the measured values of an IEQ variable from the highest to the lowest over the entire observation period. The proportion of time the variable equals or exceeds a given value is then calculated using the following formula, as defined in Publication 5, see Equation (4):

$$P(x \geq x_i) = \frac{m}{N+1} \quad (4)$$

where P is the percentage of exceedance, x is the monitored IEQ indicator (e.g., CO_2 concentration, $PM_{2.5}$ level, temperature, etc.), x_i is the i-th observatoin after sorting, m is the number of samples greater than or equal to that observation, and N is the total number of observatoins. The use of $N + 1$ in the denominator avoids boundary probabilities of 0 or 1, yielding a more reasonable exceedance distribution. This probability reflects the share of time during which the indicator exceeds a given value and is used to plot the duration curve.

The resulting duration curve provides a statistical characterization of the relationship between an IEQ variable's magnitude and the percentage of time it is equaled or exceeded. This offers an intuitive view of the distribution and persistence of IEQ over time, facilitating the identification and comparison of extreme conditions.

This method is applied separately to the spring and autumn semester datasets for each IEQ parameter to reveal seasonal differences. The analysis is performed on data filtered for occupied periods, as determined by the methods described in Section 2.3.4, to ensure the assessment reflects conditions when spaces are in use. The duration curves for each parameter and space type are plotted and compared against the critical reference values outlined in Table 3 to quantify compliance rates.

Furthermore, the temporal analysis integrates occupancy data to calculate both the occupancy probability for a space type and the corresponding average IEQ conditions. The occupancy probability at a given timestamp is calculated for each space type (office, classroom, etc.) using Equation (5):

$$O_{drm/off/cls} = \frac{\sum_{i=1}^{n} O_i}{N_{drm/off/cls}} \tag{5}$$

in which, $O_{drm/off/cls}$ is the occupancy probability within a space type, n is the number of rooms with detected human presence within the same space type, O_i is a binary constant designated as the Occupancy Detection Contributor ($O_i = 1$ when presence is detected, O_i when it is not), and $N_{drm/off/cls}$ is the total number of sensors dedicated to that space type (Publication 5).

Simultaneously, the average IEQ value within the same space type at that timestamp is calculated using Equation (6):

$$\bar{X} = \frac{\sum_{i=1}^{N_{drm/off/cls}} (C_i/P_i/T_i/H_i) * D_i}{\sum_{i=1}^{N_{drm/off/cls}} D_i} \tag{6}$$

where $\bar{X}$ is the average value for a specific IEQ indicator, represented by C_i (CO_2), P_i ($PM_{2.5}$), T_i (temperature) and H_i (relative humidity). $N_{drm/off/cls}$ is the total number of sensors dedicated to a space type, and D_i is a binary constant designated as the Denominator Contributor ($D_i = 1$ for a functioning sensor, $D_i = 0$ otherwise) that ensures the average is calculated only from active sensors.

Equations (5) and (6) together enable the analysis of how average environmental conditions correlate with overall occupancy probability within a space type over time.

2.3.6 Distribution-based and diagnostic IEQ analysis

The distribution-based and diagnostic IEQ analysis follows the methodology established in Publication 5, which implements the box plot method as originally defined by McGill et al. [35]. The set of equations for the descriptive statistics used in this analysis is presented below.

The first step involves ordering a dataset of measurements for a specific IEQ indicator from low to high:

$$x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(n)} \tag{7}$$

where $x_{(1)}$ is the smallest value (minimum) and $x_{(n)}$ is the largest value (maximum) in the dataset.

The lower quartile (Q_1), median (Q_2) and upper quartile (Q_3) are defined as:

$$Q_1 = quartile(x, 0.25) \tag{8}$$

$$Q_2 = median(x) \tag{9}$$

$$Q_3 = quartile(x, 0.75) \tag{10}$$

The interquartile range (IQR) is calculated as:

$$IQR = Q_3 - Q_1 \tag{11}$$

The lower and upper fences for outlier detection are defined as:

$$L_{fence} = Q_1 - 1.5\ IQR \tag{12}$$

$$U_{fence} = Q_1 + 1.5\ IQR \tag{13}$$

An observation is identified as an outlier if:

$$x_i < L_{fence}\ or\ x_i > U_{fence} \tag{14}$$

These equations form the computational basis for the distribution-based analysis.

2.3.7 Statistical validation of diagnostic parameters

The statistical validation of the diagnostic parameters derived from the distribution-based analysis is conducted to assess the reliability of the estimates across different groups (e.g., campus, season, space type). This validation employs Student's t-distribution to construct confidence intervals for the mean value of each diagnostic parameter within a group, as defined in Publication 5. The diagnostic parameters subjected to this validation include the Seasonal Ventilation Efficacy Coefficient (λ_{season}) and the $PM_{2.5}$ Infiltration Factor (I/O ratio), which will be discussed in detail in Section 4.2.1 of the thesis.

For a diagnostic parameter calculated from a sample of n independent observations (e.g., n rooms), the 95% confidence interval for the population mean is calculated. The method uses the following equation:

$$\bar{x} \pm t_{0.975,n-1} \frac{s}{\sqrt{n}} \quad (15)$$

in which, $\bar{x}$ is the sample mean of the diagnostic parameter, s is the sample standard deviation, n is the sample size (number of rooms in the group), and $t_{0.975,n-1}$ is the critical value from Student's t-distribution [36] with $n-1$ degrees of freedom, corresponding to the 97.5th percentile.

This approach is applied to the key diagnostic parameters, such as λ_{season} and the I/O ratio, at the group level. The resulting confidence interval provides a range of plausible values for the true population mean of the diagnostic parameter within that group. A narrow confidence interval indicates high precision in the estimate, while a wide interval reflects greater uncertainty, often due to a small sample size or high variability.

The validation process involves calculating these confidence intervals for each relevant grouping of the data. This allows for a statistical comparison of group means; if the confidence intervals of two groups do not overlap, it provides evidence of a statistically significant difference between them at the 5% significance level.

This method of statistical validation ensures that the reported differences in diagnostic parameters across climatic zones and space types are not due to random sampling variation but reflect underlying performance differences, thereby strengthening the conclusions of the climate-resilient IEQ assessment (Publication 5).

2.3.8 Economic valuation of IEQ improvements

Considering the tremendous upfront input in terms of both cost and materials, improved IEQ and reduced carbon footprint might seem intuitively contradicting, not to mention its unattractive investment profile [37]. This study strives to prove otherwise by clearly monetizing both the environmental (carbon footprint reduction) and social (improved employee productivity/wellbeing) benefits of IEQ improvements using the logic communicated in the following equations:

$$Simple\ Payback\ Time = \frac{Incremental\ Cost}{Incremental\ Benefit} \quad (16)$$

where $Incremental\ Cost$ and $Incremental\ Benefit$ are calculated respectively using the following two equations:

$$Incremental\ Cost = Unit\ Area\ Renovation\ Cost * Building\ Area \quad (17)$$

$$Incremental\ Benefit = Total\ Monetized\ Productivity\ Increase + Total\ Monetized\ Energy\ Saving \quad (18)$$

For Equation (18), $Total\ Monetized\ Productivity\ Increase$ is calculated using Equation (19):

$$Total\ Monetized\ Productivity\ Increase = Employee\ Compensation * Building\ Area * Average\ Occupant\ Density * Productivity\ Increase \quad (19)$$

in which, $Productivity\ Increase$ is calculated using Equation (20):

$$Productivity\ Increase = (P_V - 1) + (P_T - 1) + 0.02 * (1 - SL) \quad (20)$$

where:

P_V as a dimensionless quantity for relative performance in relation to a default ventilation rate of 6.5L/s, pers can be approximated to a polynomial expression using ventilation rate L (measured in L/s, pers) as independent variable:

$$P_V = -0.00002L^2 + 0.0019L + 0.9901 \quad (21)$$

P_T is a dimensionless quantity for measuring productivity in relation to its maximum value of T °C, and can be calculated using the equation developed by Seppänen *et al.* [38]:

$$P_T = 0.1647524T - 0.0058274T^2 + 0.0000623T^3 - 0.4685323 \quad (22)$$

SL is a dimensionless quantity for sick leave prevalence relative to that with no ventilation [39], [40] and can be approximated using ACH (measured in 1/h) as independent variable:

$$SL = -0.0294ACH^3 + 0.2709ACH^2 - 0.8209ACH + 0.9611 \quad (23)$$

For the $Total\ Monetized\ Energy\ Saving$ in Equation (18), it is calculated using the following equation:

$$Total\ Monetized\ Energy\ Saving = Building\ Area * \sum_i e_i * P_i \quad (24)$$

in which, e_i is the unit area saving from different energy uses (e.g. electricity, heating, etc.), P_i is the respective unit price of energy.

Energy efficient retrofit is an inseparable procedure towards IEQ improvements, to this aim, it is necessary to introduce, in addition to energy saving and productivity increase, monetized unit area carbon footprint reduction, this can be calculated using marginal abatement cost (*MAC*), which is the quotient of net present value (*NPV*) divided by $Unit\ Area\ Carbon\ Reduction$:

$$MAC = \frac{NPV}{Unit\ Area\ Carbon\ Reduction} \quad (25)$$

where:

$$NPV = -B + a * \frac{1 - [1 + (i_a - i_e)]^{-n}}{i_a - i_e} \tag{26}$$

$$Unit\ Area\ Carbon\ Reduction = \sum_i E_i * f_i \tag{27}$$

For Equation (26), B is the same as $Unit\ Area\ Renovation\ Cost$ in Equation (17), a is the monetized unit area annual energy saving desginated as net cash flow, calculated using current energy price, i_a is the interest rate set at 4% per annum, i_e is the default energy price escalation set at 2% per annum, n is the number of payback years set at 20.

For Equation (27), E_i is the unit area annual energy saving from specific type of energy use, f_i is its respective emission factor. Considering the emission factor for both heating and electricity will likely decrease over time, unit area's carbon footprint reduction throughout the payback period from heating and electricity is calculated using different emission factors during different timespan within the payback period (Publication 1).

2.4 Methods for CCE

2.4.1 Pre-operation carbon footprint within a building's life cycle

The CCE category within the PICSOU framework encompasses a comprehensive set of indicators to assess a campus's carbon and energy performance, including operational carbon footprint, electricity use, heating use, and the carbon footprint of building materials for new construction and major renovation (Publication 1). While all indicators are integral to a full assessment, this section details the methodological development for the specific indicator of "carbon footprint of building materials for new construction and major renovation", which is the focus of the research presented in Publication 3. In particular, this research focuses on modules A1, A2 and A3 of the Product stage and module A5 of the Construction Process stage of building life cycle assessment (LCA), pre-operation carbon emissions (mostly occurring during modules A1, A2 and A3 of the Product stage and module A5 of the Construction Process stage) collectively contribute to a widely varying range of percentage in a building's life cycle carbon emissions depending on factors such as local grid carbon intensity, building lifespan and climate [41], [42]. Once a building is constructed, these emissions are "locked in," making their management during the design and construction phase essential for climate mitigation, especially in regions with high construction volumes [43], [44], [45], [46]. Considering the colossal growing stock of floor area under construction globally, such emissions cannot afford to be overlooked, and this is particularly true for China's building sector, whose total under-construction floor area by year 2022 had exceeded 15,563,641,000 m^2 [47].

Typically, the construction cost process in China involves investment estimation, design budget estimation, construction drawing budgeting, contract pricing, completion settlement, and final accounts on completion (all of which occur in module A5). Before the final accounts on completion, regulatory agencies are invited to conduct audits, which involve reviewing and evaluating the authenticity and legality of the entire cost of the construction project, as shown in Figure 9. If such readily available data can be utilized, the data acquisition and calculation for the carbon emissions of modules A1 through A5 (excluding A4) will be greatly simplified.

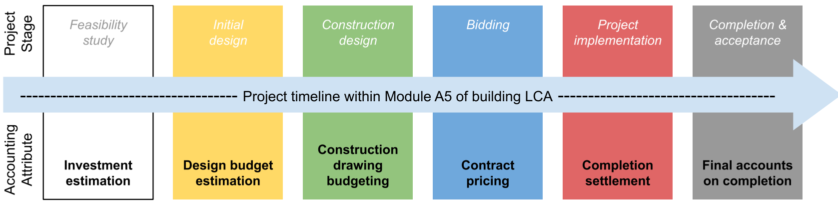


Figure 9. Project timeline within Module A5 of building LCA

The methodology for this particular PICSOU CCE indicator (carbon footprint of building materials for new construction and major renovation) is based on QCEPM, a novel regulatory model developed to simplify the estimation of embodied carbon in multi-story buildings. QCEPM was created to address the challenges of data acquisition and computational intensity associated with conventional carbon accounting methods, providing a tool for efficient regulatory oversight (see Figure 10).

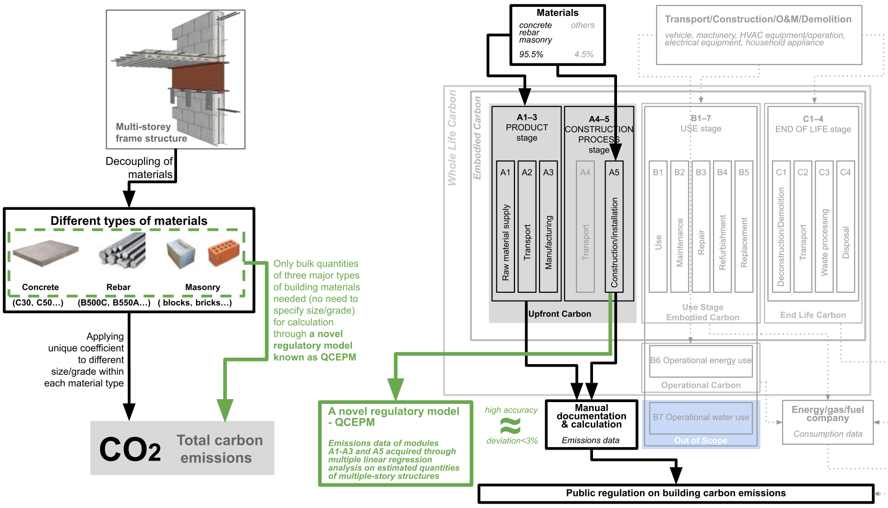


Figure 10. On the left: Comparison between the conventional calculation method (text box and arrows denoted in black) and QCEPM (dotted box, text and arrow denoted in green) within the scope of a project's workflow; On the right: Comparison between the conventional calculation method (text boxes and arrows denoted in black) and QCEPM (text box and arrow denoted in green) in terms of stages/modules covered within the scope of building LCA (text boxes and dotted arrows denoted in gray) according to ISO 21930: 2017.

2.4.2 QCEPM regression model for embodied carbon

The model utilizes a multiple linear regression (MLR) analysis, an established statistical technique for modeling the relationship between multiple independent variables and a dependent variable, which has been widely used in problem solving for environment or engineering related topics [48], [49], [50].

The general form of the MLR model is expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_i x_m + \varepsilon \quad (28)$$

where y is the dependent variable, ε is the random error, β_0, β_1, ..., β_i are the regression coefficients, and x_1, x_2, ..., x_m represent a set of m independent variables that are both measurable and controllable.

For a sample of n observations, the relationship for each observation i is given by:

$$y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_2 x_3 + \cdots + \beta_m x_{im} + \varepsilon_i \quad (29)$$

in which, i = 1, 2, ..., n, each of the ε_i is independent, and $\varepsilon_i \sim N(0, \sigma^2)$.

Thus, we obtained the following formulae:

$$\beta = (\beta_0, \beta_1, \cdots, \beta_m)^T, \ \varepsilon = (\varepsilon_0, \varepsilon_1, \cdots, \varepsilon_m)^T, \ Y = (y_0, y_1, \cdots, y_m)^T \tag{30}$$

$$X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1m} \\ 1 & x_{21} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{31}$$

Equations (30) and (31) can also be expressed in the following matrix:

$$y = X\beta + \varepsilon \tag{32}$$

We then assumed full column rank for the matrix, solving for $X^T Y = (X^T X)\hat{\beta}$, yielded $\hat{\beta} = (X^T X)^{-1} X^T Y$.

Thus, the unbiased estimate of $\hat{\sigma}^2$ can be expressed as follows:

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{m} x_{ij} \hat{\beta}_j \right)^2}{n - m - 1} \tag{33}$$

In the specific application of QCEPM, the dependent variable E is designated as the total embodied carbon emissions, and the independent variables are designated as the quantities of concrete (C), rebar (R), and masonry (M). Thus, the applied model can be expressed as:

$$E = \beta_0 + \beta_1 C + \beta_2 R + \beta_3 M + \varepsilon \tag{34}$$

2.5 Methods for transportation

2.5.1 Transportation indicators

The transportation category within the PICSOU framework addresses Scope 3 carbon emissions, focusing specifically on commuting to and from the university campus by its population, defined as the sum of all employees, students, and staff (Publication 1). The primary KPI for this category is the carbon footprint from commuting trips, measured in t CO_2eq/(person · a). This indicator is designed to identify the major contributors to commuting emissions, thereby providing an evidential basis for adjustments in policymaking and the planning of transit nodes and campus facilities. The assumption is that most people prefer walking distances of no more than 400 meters for casual destinations and 800 meters for regular commutes [51].

The general equation for calculating carbon footprint from commuting can vary depending on the specific factors considered, yet a commonly adopted equation can be described as follows:

$$E = \sum E_i \tag{35}$$

where E is the total carbon footprint, E_i is the carbon footprint from each mode of commuting, which can be expressed using Equation (36):

$$E_i = D_i \times EF_i \tag{36}$$

in which, D_i is the distance (km) or time (min) traveled (depending on the workflow) and EF_i is the carbon emission factor for the corresponding commuting mode.

2.5.2 Multi-source commuting data acquisition

This study employed two distinct methodological approaches to quantify the commuting-related carbon footprint for the identical physical boundary of TalTech's Mustamäe campus over the same temporal scope (the year 2022). The first approach, designated as the conventional approach, relied on established methodologies involving historical data and a three-year average of survey statistics [52]. The second approach constituted a novel workflow that leveraged two complementary, weighted sources of legally collected and anonymized traffic data. This methodology utilized unique ICT-based algorithms from the Telia Crowd Insight [53] and Fyma [54] platforms to generate activity data, which was subsequently converted into emissions figures. The resulting carbon footprint calculated through this novel approach was formally documented in TalTech's 2022 Greenhouse Gas (GHG) inventory [55]. As proprietary intellectual properties, the algorithm of both Telia Crowd Insight and Fyma cannot be fully disclosed, however their respective working principles in comparison with the conventional data workflow can be illustrated in Figure 11:

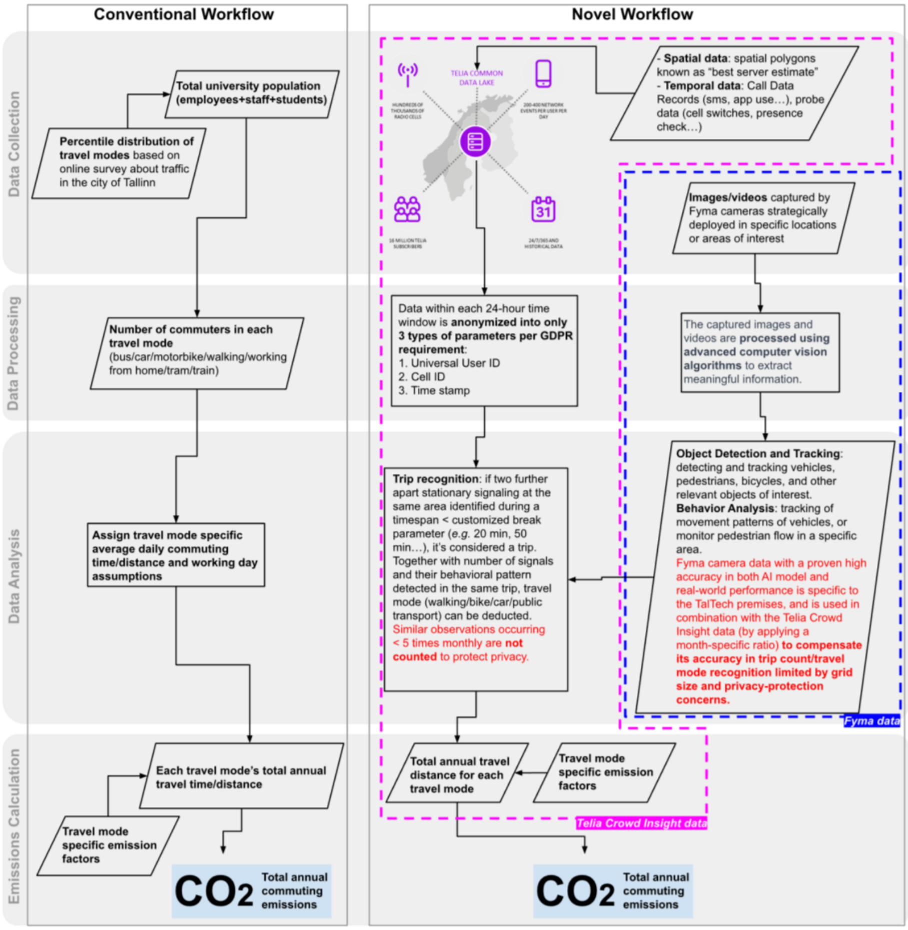


Figure 11. Working principles and data workflow of two alternative approaches

3 Results

This chapter presents the empirical results derived from application of the PICSOU framework across its major assessment categories discussed in this thesis (space efficiency and learning environment, IEQ, CCE, and transportation). Findings are reported sequentially following the methodological structure established in Chapter 2. Each section documents the observed performance patterns at TalTech or/and CDJCC campus, without interpretative synthesis or normative evaluation, establishing a factual basis for discussion in Chapter 4.

3.1 The PICSOU framework: categories and indicators

The PICSOU framework presented here consolidates the categorical structure and indicator definitions initially developed and reported in Publication 1.

On the basis of the analysis presented in Sections 1.1 - 1.3, this study devised a diagnostic tool by identifying a simple six-category framework with minimum numbers of KPIs designated as PICSOU, whose metrics are dedicated to facilitating informed decision-making towards achieving environmental goals on university campuses from a climate-neutral or/and cost-benefit perspective. In this study, only the first four of the six PICSOU categories are evaluated and validated, the remaining two categories, whose indicators possess equal importance in terms of their distinctive environmental and economic impact, are omitted in this study due to their limited effect on the overall results of the case study at the TalTech campus – the same campus based on which the structure and content of the PICSOU framework was initially proposed. All categories of the PICSOU framework correspond to relevant SDGs, whose principle is in line with the three pillars of sustainability [56] as shown in Figure 1. A break-down of each PICSOU category's corresponding indicators are listed in Table 6.

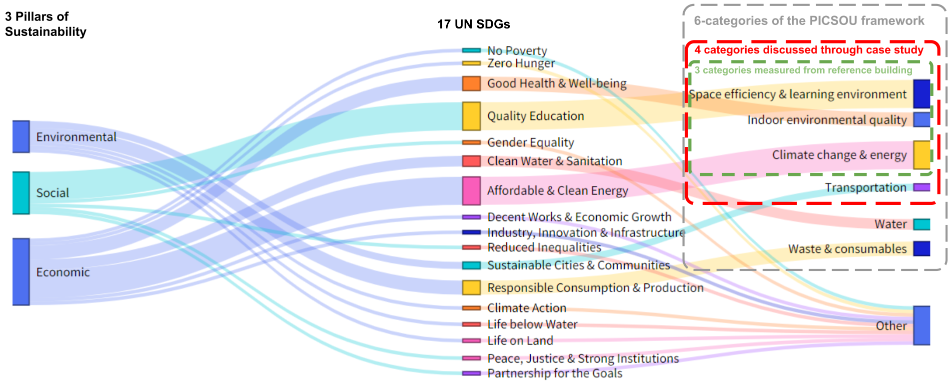


Figure 12. The correlation between the 3 Pillars of Sustainability, 17 Sustainable Development Goals of the United Nations, and the PICSOU framework

Table 6. Categories and indicators of the PICSOU framework

Sustainability category	Key performance indicators (KPIs)
1. Space efficiency & learning environment	1.1: Auditoriums and other learning spaces measured by m^2 per student 1.2: Teaching laboratory m^2 per student 1.3: Office & meeting rooms per staff 1.4: Total space per person (staff + students) 1.5: Self-learning and group working spaces (informal learning seats), number of informal seats per formal seat 1.6: Sports facility per person (staff + students) 1.7: Ratio of parking space (including underground parking) per person
2. IEQ	2.1: Indoor air quality, category I and II spaces, % 2.2: General thermal comfort, category I and II spaces, %
3. Climate change & energy	3.1: Carbon footprint, tCO_2/(person · a) 3.2: Electricity use, kWh/(person · a) 3.3: Heating use, kWh/(person · a) 3.4: Primary energy use, kWh/(m^2. a) 3.5: Renewable energy export, kWh/(m^2. a) 3.6: Carbon offset, tCO_2/(person · a) 3.7: Carbon footprint of building materials for new construction and major renovation, $kgCO_2$-eq/m^2
4. Transportation	4.1: Carbon footprint from work trips, business trips (no data), inside campus transport (no data), tCO_2/(person · a)
5. Water	5.1: Water use, m^3/(person · a) 5.2: Capacity for stormwater runoff absorbance, m^3/a
6. Waste & consumables	6.1: Recycled waste streams, kg or m^3/(person · a) 6.2: Electronic waste, €/(person · a) 6.3: Organic/food waste, kg/(person · a) 6.4: Toxic waste, m^3/a

3.2 Space efficiency and learning environment

3.2.1 Campus space inventory

The space efficiency and learning environment category of the PICSOU framework serves both as an audit on the current space arrangement of the campus as well as a point of interest in discovering the probable correlation between availability and quality of learning space, as decision-makers and users of space often experience things differently [57]. Table 7 entails a complete space inventory of the TalTech Mustamäe campus premises (see Figure 13) as of year 2022 (Publication 1).

Table 7. Campus summary form of TalTech's Mustamäe campus

NET USABLE AREA (*NUA*): **85.0%** *100%* 115194 m² 3644 spaces												**15.0%**
NET ASSIGNABLE AREA(NAA): **56.9%** *66.9%* 77064.6 m² 2371 spaces									NON-ASSGNABLE AREA (NASA) **28.1%** *33.1%* 38129.4 m² 1273 spaces			
Percentage by **gross area**	**10.1%**	**1.9%**	**13.1%**	**12.6%**	**3.8%**	**3.6%**	**9.4%**	**0.2%**	**1.8%**	**18.9%**	**7.4%**	
Percentage by *NUA*	*11.9%*	*2.3%*	*14.8%*	*17.9%*	*4.5%*	*4.2%*	*11.0%*	*0.3%*	*2.1%*	*22.3%*	*8.7%*	
Average space size	52.7 m²	56.8 m²	35.4 m²	19.2 m²	114.7 m²	107.5 m²	31.9 m²	18.7 m²	5.2 m²	47.5 m²	38.2 m²	
Number of spaces	261	46	481	1077	45	45	396	20	470	540	263	
Space category	CLASSROOMS 13741.9 m²	GENERAL USE 2614.8 m²	LABORATORIES 17041.6 m²	OFFICES 20635.2 m²	SPECIAL USE 5159.6 m²	STUDY SPACE 4838.9 m²	SUPPORT 12659.5 m²	UNCLASSIFIED 373.7 m²	BUILDING SERVICES 2433.8 m²	CIRCULATION 25644.7 m²	MECHANICAL 10050.9 m²	STRUCTURAL GROSS AREA 20328.4 m²
Physical scope: 18 buildings, 94 floor plans; 38 departments												

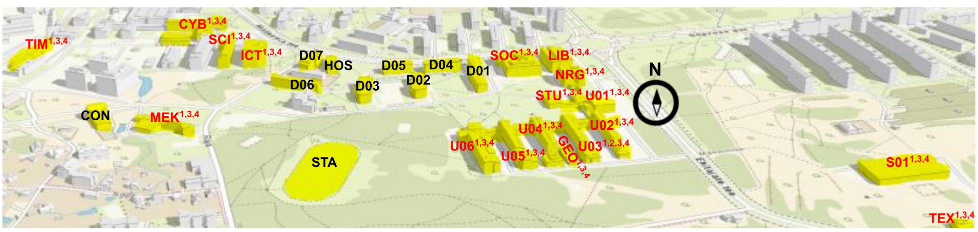


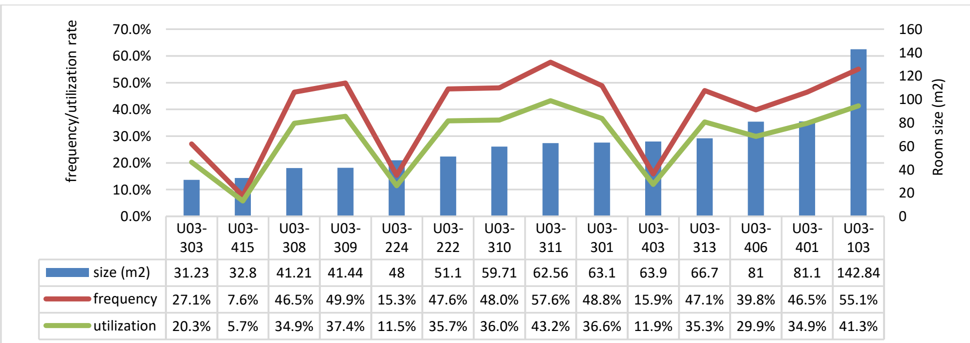
Figure 13. Map of TalTech's Mustamäe campus premises (color coded in yellow), buildings marked with red text and superscripts consist of mostly teaching/learning/laboratory/office spaces, which are discussed in Publication 1, the superscripts indicate under which of the 6 categories of the PICSOU framework this building is studied; buildings with black text consist of dormitories, newly completed research facility and stadium, and are not discussed in Publication 1.

3.2.2 Average space size discrepancy

It can be observed from Table 7 that, study spaces have a rather large average size of 107.5 m² compared to all other space types, which does not reflect reality, this outlier can be attributed to the fact that most formal study spaces are located in the library, where reading halls can have exceptionally ample space (e.g. library's room 222 alone has an area of 1137.3 m²). In reality, group study spaces at TalTech are usually sized around 10 m² and individual study spaces < 3 m².

3.2.3 Learning space utilization patterns

Basing off the statistics in the campus summary form, further mapping of the learning space utilization helps streamline the maintenance activity and minimize the operational cost/carbon emission by identifying under-occupied learning spaces. In the case study carried out in Publication 1, we singled out all rooms in the reference building of U03 under the classroom category in Table 7 from TalTech's online room register system, and accessed each classroom's booking schedule in the study information system to calculate their respective weekly total booked hours – before subsequently solving for their individual utilization rate using Equation (1). Figure 14 below features the learning space utilization in a reference building, calculated using a default occupancy value of 75% and exhibits a clear linear correlation between frequency of use and overall utilization.



	U03-303	U03-415	U03-308	U03-309	U03-224	U03-222	U03-310	U03-311	U03-301	U03-403	U03-313	U03-406	U03-401	U03-103
size (m2)	31.23	32.8	41.21	41.44	48	51.1	59.71	62.56	63.1	63.9	66.7	81	81.1	142.84
frequency	27.1%	7.6%	46.5%	49.9%	15.3%	47.6%	48.0%	57.6%	48.8%	15.9%	47.1%	39.8%	46.5%	55.1%
utilization	20.3%	5.7%	34.9%	37.4%	11.5%	35.7%	36.0%	43.2%	36.6%	11.9%	35.3%	29.9%	34.9%	41.3%

Figure 14. Learning space utilization in reference building U03

3.2.4 Parking space use efficiency

Parking space efficiency is determined by a metric designated as the number of parking spaces per person. Following the workflow illustrated in Figure 4, we adopted the methods used by the LEEDv4 BD+C [29] and picked the smaller (i.e., more stringent) value between the compliant number of per-person parking space set by ITE (the U.S. Institute of Transportation Engineers) [30] and the number set by the city of Tallinn's local regulations [31] as the reference base. Then we applied a 40% reduction factor to the reference base, solving for the target number of total parking spaces for TalTech's Mustamäe campus, which is much lower than the currently available total number of parking spaces on campus, indicating a clear potential for parking space reduction. Dividing such target number by the total university population yielded the target number of per-person parking space, which is 0.05 parking space per person.

3.3 IEQ

3.3.1 TalTech IEQ baseline results

With the reference building of U03, which is a four-story building with 61 rooms consisting auditoriums, offices and laboratories totaling 6482 m^2 of NUA (net usable area), we calculated each room's capacity, ventilation rate (L/s, pers.), air change rate (1/h) and indoor environmental category per EN 16789-1 standard [32], such results not only serve as the status-quo of the current indoor air quality of the rooms within the reference building (see Table 8), but also provide the basis for calculating the pre-retrofit P_V value and SL value of each room using Equation (21) and Equation (23). Since there was no complete annual documentation of hourly room temperature of all rooms within reference building U03, we chose to first simulate pre and post retrofit room temperature under typical operation scenario using an IDA ICE model of U03 (see Figure 15), each room's operating temperatures (see Figure 16 and Figure 17 for the example of operating temperature distribution and duration curve under different simulated cooling scenarios) from the simulation results were then fed into Equation (22) to solve for their respective pre and post retrofit P_T (Publication 1).

Table 8. Overview of TalTech Mustamäe campus' baseline and target IEQ values per EN-16798 standard (Publication 1)

PICSOU category	Key performance indicators (KPIs)	Data source/update frequency	Target value	TalTech baseline value from case study
2. IEQ	Indoor air quality, category I and II spaces, %	Monitored or simulated sub-hourly values and booking schedule, updated monthly	80% category I, 20% category II	54% Category I, 29.5% category II, 16.5% category III (U03)
	General thermal comfort, category I and II spaces, %	Monitored or simulated sub-hourly values and booking schedule, updated monthly	80% category I, 20% category II	0% category I, 25.9% category II, 74.1 category III (U03)

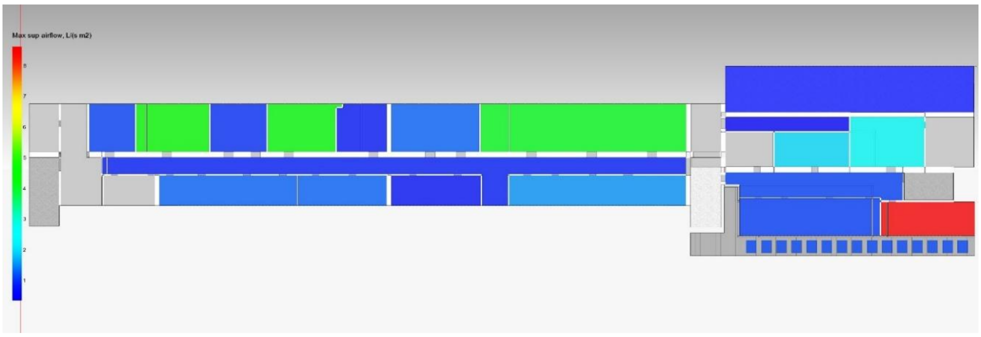


Figure 15. Map of maximum supply air flow on 2nd floor of reference building U03 based on IDA ICE simulation of the pre-retrofit condition

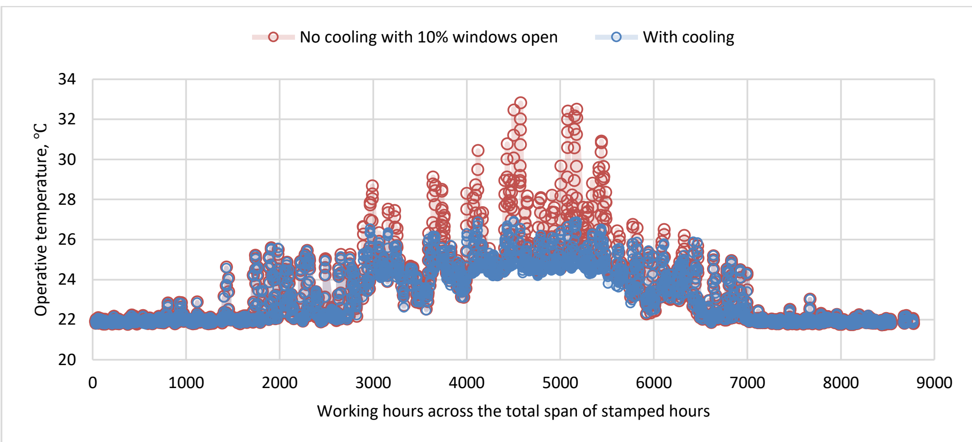


Figure 16. Reference room's distribution of operating temperatures under different cooling scenarios

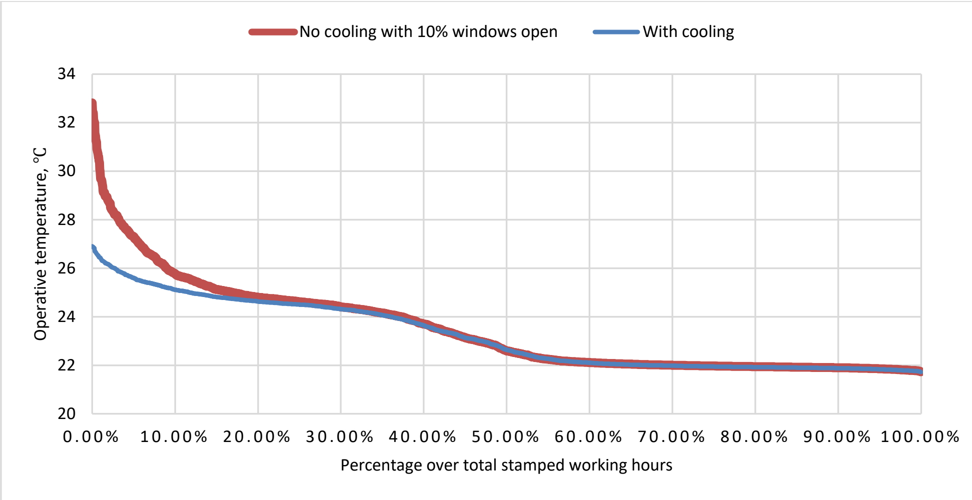


Figure 17. Reference room's duration curve of operating temperatures under different cooling scenarios

3.3.2 Economic valuation of IEQ improvements

For monetized productivity increase, we calculated each room's target post-retrofit P_V- SL pair by assigning the optimal air supply rate and ventilation rate. We then used the difference in each room's pre, and post retrofit P_V- SL pair joined by the pre and post retrofit P_T value in Equation (20) to solve for the total quantified annual productivity increase percentage from increased ventilation, reduced sick leave prevalence and improved thermal comfort. Combining all the results from Equation (20) into Equation (19), we obtained reference building U03's total monetized annual productivity increase from the above-mentioned IEQ indicator improvements, dividing this value by the total net area of U03, we obtained the monetized annual unit area productivity increase as shown in Figure 18 (Publication 1).

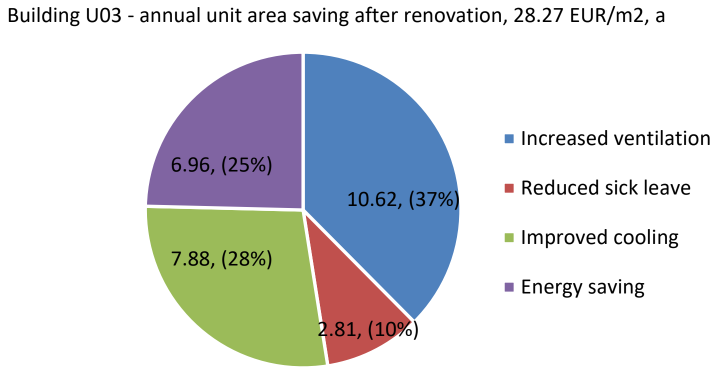


Figure 18. Breakdown of reference building U03's post retrofit annual unit area monetary benefit

Pertaining to the environmental benefit of IEQ and energy efficiency-driven retrofit, we calculated the cost effectiveness for U03's retrofit using Equations (25)(26) and (27), and obtained an MAC value of -1160 €/(t CO_2eq · m^2).

3.3.3 CDJCC IEQ measurement results

As a cross-climate validation and adaptation of the IEQ category under the PICSOU framework, which was initially proposed entirely based on temperate climate context, IEQ testing at CDJCC, a campus located in subtropical monsoon climate was featured by short-term, high-resolution monitoring campaigns in a naturally ventilated building stock. Building on the winter pilot introduced in Publication 4 and the subsequent spring-semester monitoring design in Publication 5, custom-built sensors were deployed across 6 dormitories, 2 offices, 4 classrooms and up to 2 outdoor locations per semester. Each sensor recorded CO_2, PM2.5, air temperature and relative humidity at 1-minute intervals, together with real-time occupancy status from an integrated FMCW radar module, yielding more than 3.8 million records across the 2024 autumn and 2025 spring semesters.

As initial verification of the fidelity of the custom-built sensor units' integrated FMCW radar module, we plotted the duration curve of CO_2 concentration under different occupancy probabilities across all space types (see Figure 19). The results indicate a positive correlation between average CO2 concentration and occupancy probability across all space types, which aligns with the established principle that CO2 level serves as a reliable proxy for human presence. An anomaly is observed in dormitories, where the duration curves for 83% and 67% occupancy probabilities largely overlap and exceed the curve for 100% occupancy probability. This inverse relationship can be attributed to the small spatial volume of dormitories; higher occupancy likelihood increases the probability of door or window opening for natural ventilation, thereby reducing CO_2 accumulation. In contrast, larger spaces like offices and classrooms exhibit a stronger positive correlation, likely due to reduced ventilation interventions stemming from social inhibition among occupants. The overall realism of the duration curves validates the synchronous data collection of the FMCW radar module and its IEQ suite counterpart, confirming the FMCW radar module was working as intended (Publication 5).

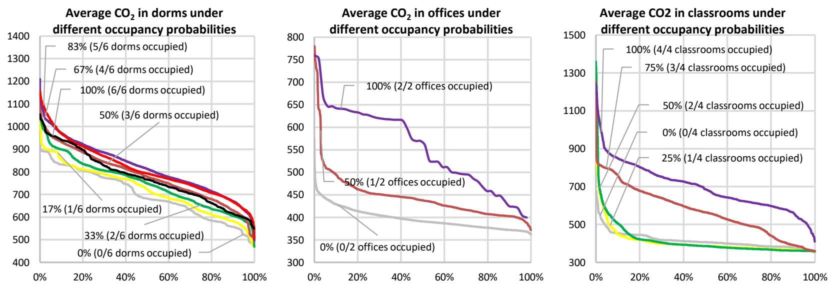


Figure 19. Average CO_2 concentration in different space types under different occupancy probabilities

Upon initial verification of the fidelity of documentation of real-time occupancy status in parallel to standard IEQ suite (CO_2, $PM_{2.5}$, temperature), we plotted each room's occupied CO_2/$PM_{2.5}$/temperature duration curve for both the autumn 2024 semester and the spring 2025 semester (see Figure 20 and Figure 21), outliers in the duration curves are not visually prominent but contribute greatly to range of values, hence were better represented using box plots (see Figure 22).

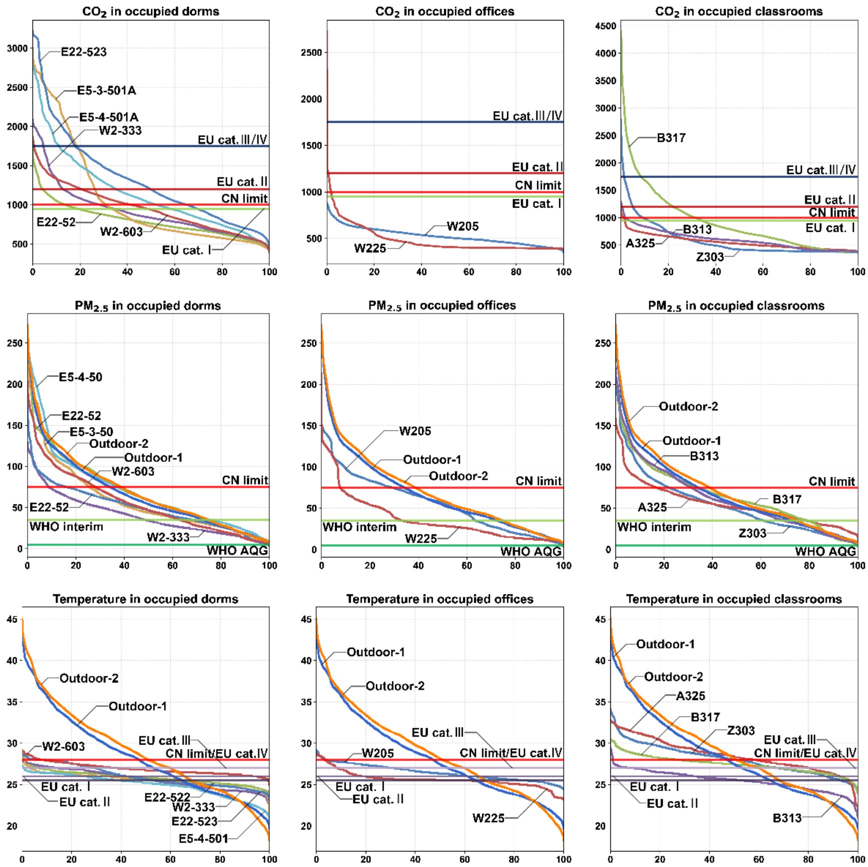


Figure 20. CDJCC spring semester duration curves under occupancy, by space type

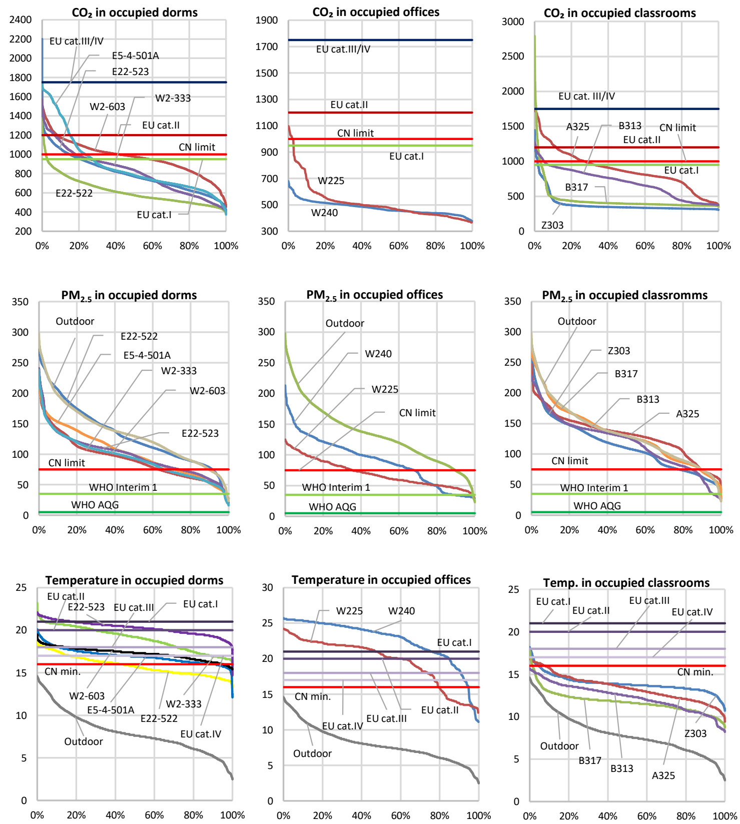


Figure 21. CDJCC autumn semester duration curves under occupancy, by space type

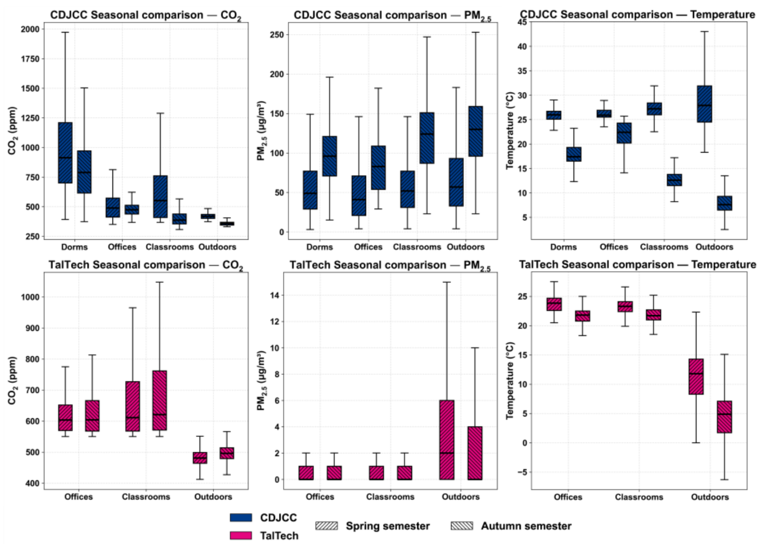


Figure 22. IEQ value ranges on CDJCC and TalTech campus across space types and semesters

In the spring semester, the median CO_2 concentrations for dormitories/offices/classrooms/outdoors were 913/489/552/419 ppm, ranked dormitories > classrooms > offices. Dormitory box ranges exceeded the EU Cat. II summer threshold of 1,200 ppm in 2 % of observations, while all other space types remained below applicable reference limits. Dormitories and classrooms exhibited wider typical CO_2 intervals, indicating stronger fluctuations and occasional extreme values. In the autumn semester, median CO_2 concentrations for dormitories/offices/classrooms/outdoors were 789/474/388/359 ppm. Typical indoor distributions for all space types remained below the CN winter limit (1000 ppm), with dormitories again exhibiting the broadest box ranges and thus the greatest variability. Comparing the spring and autumn semesters, both median values and typical CO_2 ranges were lower in autumn than in spring for most space types, while office concentrations showed minimal seasonal change.

During the spring semester, median $PM_{2.5}$ concentrations for dormitories/offices/classrooms/outdoors were 49/41/52/57 µg/m³. Exceedance of the CN summer threshold (75 µg/m³) occurred in 4 % of dormitory observations, whereas all other space types remained below this limit. During the autumn semester, median $PM_{2.5}$ concentrations increased to 96/83/124/130 µg/m³, ranked classroom > dormitory > office. Typical concentrations exceeded the WHO Interim Target-1 (35 µg/m³) in 92 % of dormitories, 62 % of offices, and 100 % of classrooms. Comparing the spring and autumn semesters, both medians and typical $PM_{2.5}$ ranges were higher in autumn than in spring, reflecting increased background concentrations and stronger infiltration during the colder monitoring period.

Spring median indoor temperatures were 23.9 °C (offices) and 23.3 °C (classrooms), with outdoor medians of 11.8 °C. Typical distributions remained below the EU Cat. I summer upper threshold (25.5 °C). Autumn median temperatures declined to 21.8 °C (offices), 21.7 °C (classrooms) and 4.9 °C (outdoors). While most distributions exceeded the EU Cat. I winter lower threshold (21 °C), 20 % of office observations fell below this limit. Comparing the spring and autumn semesters, both median values and typical temperature ranges were lower in autumn than in spring, consistent with declining outdoor thermal boundary conditions (Publication 5).

3.3.4 TalTech IEQ measurement results

Similar to the CDJCC campus, for TalTech's Mustamäe campus, we plotted each room's occupied CO_2/$PM_{2.5}$/temperature duration curve for both the autumn 2024 semester and the spring 2025 semester (see Figure 23 and Figure 24), less visually prominent outliers in the duration curves contributing to range of values, are represented using box plots in Figure 22.

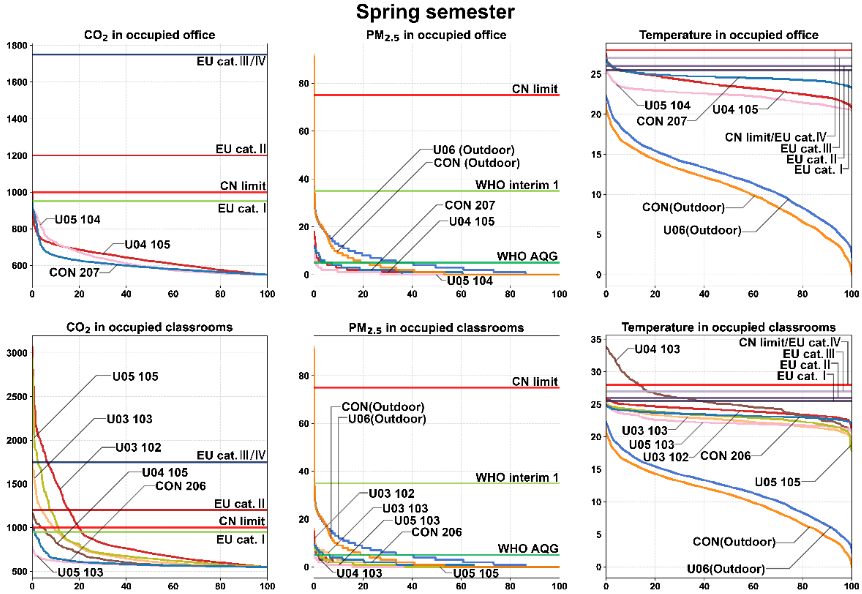


Figure 23. TalTech spring semester duration curves under occupancy, by space type

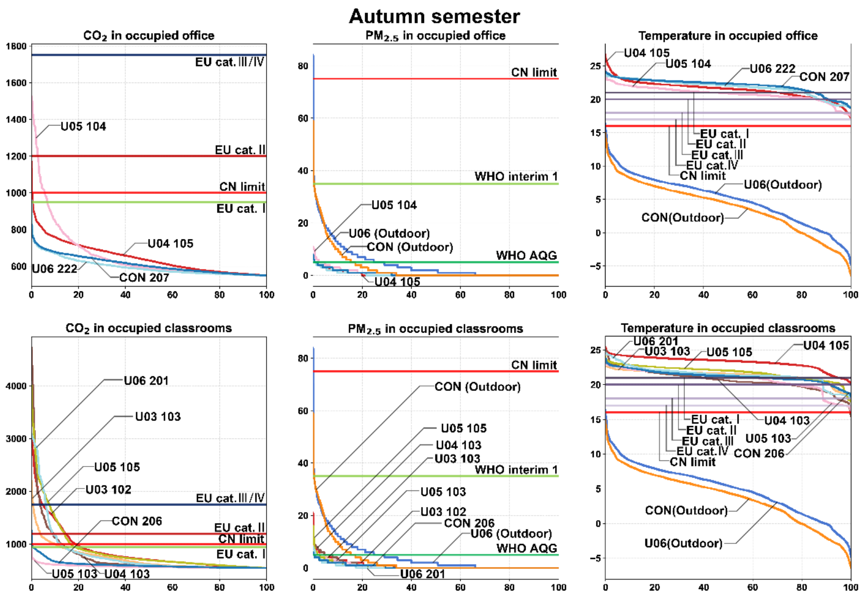


Figure 24. TalTech autumn semester duration curves under occupancy, by space type

During the spring semester at TalTech, median CO_2 concentrations for offices/classrooms/outdoors were 604/611/481 ppm. No substantial inter-space differences were observed in median values, and typical concentration intervals were similar across space types. All monitored spaces remained below the EU Category I limit (950 ppm), although classrooms demonstrated a relatively extended box range with a low-positioned median, indicating greater within-interval fluctuation and occasional high-end values. In the autumn semester, the corresponding CO_2 medians were 604/621/496 ppm, again with minimal variation between space types. Typical concentration intervals for all monitored spaces continued to remain below the EU Category I threshold (950 ppm) and exhibited no major deviation from spring patterns. Comparison between the spring and autumn semesters indicated that the upper quartiles of the autumn distributions were marginally higher than their spring counterparts despite unchanged mechanical ventilation strategies, which was attributed to reduced outdoor activity during colder weather and the associated increase in indoor occupancy density.

During the spring semester, median $PM_{2.5}$ concentrations for offices/classrooms/outdoors were 0/0/2 μg/m³, with no appreciable differences observed between space types. Typical concentration intervals across all indoor and outdoor spaces remained below the WHO Air Quality Guideline (5 μg/m³). In the autumn semester, corresponding $PM_{2.5}$ medians were 0/0/0 μg/m³, again showing no substantial differences among monitored spaces, and typical PM2.5 intervals for all locations remained below the WHO guideline threshold (5 μg/m³). Comparison between spring and autumn indicated that outdoor typical PM2.5 ranges were marginally higher during spring, whereas indoor distributions remained comparatively stable across both seasons, demonstrating the sustained pollutant-removal effectiveness of the mechanical ventilation filtration systems deployed at TalTech.

In the spring semester, median air temperatures at TalTech for offices/classrooms/outdoors were 23.9/23.3/11.8 °C, with minimal variation among monitored space types. Typical indoor temperature ranges across all spaces remained below the EU Category I summer upper limit (25.5 °C), and distributions were uniformly narrow, indicating constrained thermal variability during occupied periods. In the autumn semester, median temperatures declined to 21.8/21.7/4.9 °C for offices, classrooms, and outdoor environments, respectively, again showing minimal inter-space differences. Most typical temperature ranges exceeded the EU Category I winter lower threshold (21 °C), except for offices, where 20% of observations fell below this limit. Across all monitored spaces, temperature fluctuations remained comparatively restrained. Cross-seasonal comparison demonstrated that both median temperature values and typical ranges were lower in the autumn semester than in spring. Seasonal variation was more pronounced outdoors than indoors, underscoring the buffering effect of TalTech's mechanical ventilation systems in stabilizing indoor thermal environments (Publication 5).

3.3.5 Cross-campus IEQ performance comparison

For cross-campus IEQ performance comparison, we plotted box plots for all IEQ indicators at both campuses (see Figure 25), whose side-by-side comparison can be found in Table 9.

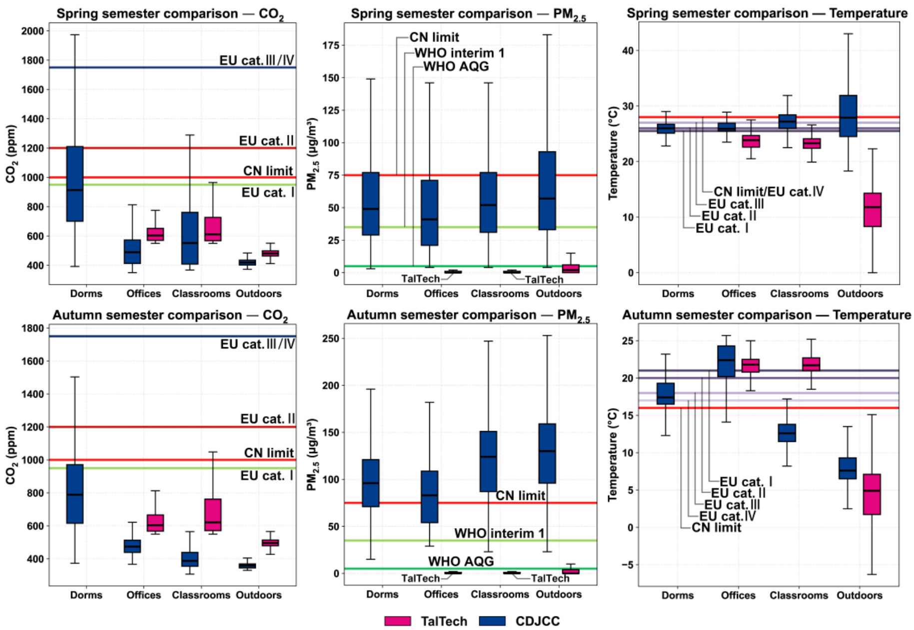


Figure 25. Cross-campus seasonal IEQ comparison within space types

Table 9. Cross-campus IEQ comparison featuring median, IQR and compliance based on max. 5% exceedance tolerance according to the TAIL (thermal environment, acoustic environment, indoor air, and luminous) Scheme [58], which is in line with European Commission's latest guidance by the Energy Performance of Buildings Directive (EPBD) [59].

Campus (Semester)	Space Type	CO_2, ppm (Med; IQR; Minimum compliance)	$PM_{2.5}$, μg/m³ (Med; IQR; Minimum compliance)	Temperature, ℃ (Med; IQR; Minimum compliance)
CDJCC (Spring)	Dormitory	913; 509; failed EU cat.III	49; 48; exceeded CN limit	26.0; 1.8; CN upper limit
	Office	489; 160; EU cat.I	41; 50; exceeded CN limit	25.9; 1.9; CN upper limit
	Classroom	552; 352; EU cat.III	52; 46; exceeded CN limit	27.2; 2.4; exceeded CN upper limit
	Outdoor	419; 72; N/A	57; 60; exceeded CN limit	27.9; 7.4; N/A
TalTech (Spring)	Office	604; 84; EU cat.I	0; 1; WHO AQG	23.9; 2.2; EU cat.I
	Classroom	611; 159; EU cat.III	0; 1; WHO AQG	23.3; 1.8; EU cat.I
	Outdoor	481; 72; N/A	2; 6; WHO Interim 1	11.8; 6.0; N/A
CDJCC (Autumn)	Dormitory	789; 355; EU cat.III	96; 50; exceeded CN limit	17.4; 2.8; exceeded CN lower limit
	Office	474; 74; EU cat.I	83; 54.8; exceeded CN limit	22.4; 4.1; exceeded CN lower limit
	Classroom	388; 84; CN limit	124; 64; exceeded CN limit	12.6; 2.3; exceeded CN lower limit
	Outdoor	359; 52; N/A	130; 63; exceeded CN limit	7.6; 2.8; N/A
TalTech (Autumn)	Office	604; 98; EU cat.I	0; 1; WHO AQG	21.8; 1.7; EU cat.III
	Classroom	621; 191; EU cat.II	0; 1; WHO AQG	21.7; 1.7; EU cat.III
	Outdoor	496; 52; N/A	0; 4; WHO Interim 1	4.9; 5.4; N/A

During the spring semester, outdoor CO_2 typical intervals and medians at TalTech were slightly higher than at CDJCC, and office and classroom medians were slightly higher at TalTech, while CDJCC exhibited longer typical CO_2 intervals, indicating greater intra-range variability and more pronounced high-end excursions; in the autumn semester, TalTech again showed slightly higher outdoor typical intervals and medians, whereas the classroom median at TalTech sat lower within its typical interval relative to CDJCC, indicating continued high-end fluctuation tendencies; these cross-campus differences correspond to mechanical ventilation at TalTech providing stronger concentration control relative to mixed-mode ventilation at CDJCC, which produced broader CO_2 distributions.

During the spring semester, the outdoor $PM_{2.5}$ typical interval and median at CDJCC were markedly higher than at TalTech, with indoor concentrations at both campuses following the same spatial trend, while indoor typical intervals and medians remained lower than outdoor values; during the autumn semester the cross-campus pattern remained consistent with spring, with indoor $PM_{2.5}$ distributions governed primarily by outdoor infiltration and supplementary particulate reduction provided under mechanical ventilation filtration at TalTech relative to mixed-mode operation at CDJCC.

In the spring semester, CDJCC's outdoor typical temperature interval and median were significantly higher than TalTech's, and office and classroom medians and typical intervals were slightly higher at CDJCC, with indoor temperatures demonstrating stronger coupling to outdoor conditions; in the autumn semester, CDJCC again showed slightly higher outdoor medians and typical intervals, while TalTech experienced greater outdoor temperature fluctuation, and indoors CDJCC offices exhibited slightly higher medians with longer typical intervals, indicating enhanced variability and increased exposure to low-temperature extremes, whereas CDJCC classrooms recorded markedly lower typical intervals and medians than TalTech, corresponding to a compressed temperature distribution with lower central tendency and reduced typical range; overall cross-campus contrasts indicate more stable indoor temperature control with weaker climatic coupling at TalTech relative to weaker stability and stronger outdoor dependency at CDJCC (Publication 5).

3.4 CCE

3.4.1 Operational energy and carbon baseline at TalTech

Operational emissions within PICSOU's CCE category were quantified from metered heating and electricity use using locally representative emission factors for Tallinn: 0.11 t CO_2eq/kWh for district heating and 0.717 t CO_2eq/kWh for electricity [60]. These coefficients were applied to calculate unit-area and per-capita carbon indicators. Construction-stage emissions were required to be assessed through life-cycle assessment methods, as material decarbonization may provide up to 20% reduction in total building carbon footprints under materials-neutral substitution strategies [61].

Campus-level operational energy use was normalized by floor area, yielding specific heating and electricity use of 176 kWh/($m^2 \cdot$ a) and 115 kWh/($m^2 \cdot$ a) respectively (see Figure 26 and Figure 27). The baseline operational carbon footprint was calculated as 1.30 tCO_2/(person · a) across 18 buildings, with commuting emissions included within the accounting boundary.

Disaggregated per-user indicators showed electricity use of 1045 kWh/(person · a) and heating use of 1265 kWh/(person · a) for the same 18-building dataset. Primary energy performance calculated using conversion factors of 1.0 for natural gas, 0.65 for district heating, and 2.0 for electricity, reached 349 kWh/($m^2 \cdot$ a) across 18 buildings on the campus (see

Table **10**).

On-site renewable energy export remained < 1 kWh/m^2 a, indicating negligible net contribution to operational energy use. Carbon offset mechanisms were not applied during the study period, corresponding to an offset level of 0 tCO_2/(person · a) (Publication 1).

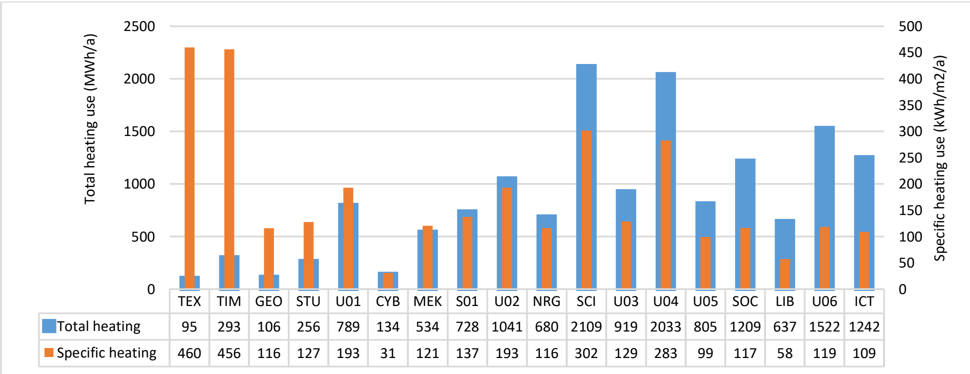


Figure 26. Total and specific heating use of selected campus buildings

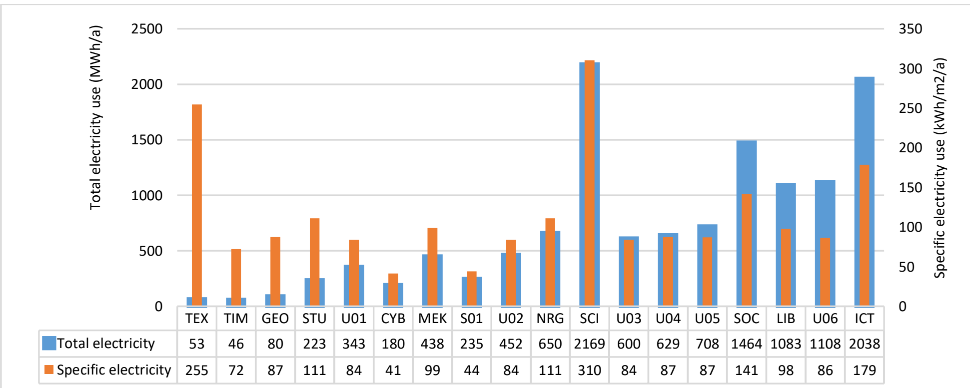


Figure 27. Total and specific electricity use of selected campus buildings

Table 10. Overview of TalTech Mustamäe campus' target and baseline CCE values (Publication 1)

PICSOU category	Key performance indicators (KPIs)	Data source/update frequency	Target value	TalTech baseline value from case study
3. Climate change & energy	Carbon footprint, $tCO_2/(person \cdot a)$	Calculated from metered monthly values, updated annually	To be specified locally	1.30 $tCO_2/(person \cdot a)$ (18 buildings, includes transportation)
	Electricity use, $kWh/(person \cdot a)$	Calculated from metered monthly values, updated annually	To be specified locally	1045 $kWh/(person \cdot a)$ (18 buildings)
	Heating use, $kWh/(person \cdot a)$	Calculated from metered monthly values, updated annually	To be specified locally	1265 $kWh/(person \cdot a)$ (18 buildings)
	Primary energy use, kWh/m^2 a	Calculated from metered monthly values, updated annually	To be specified locally	349 kWh/m^2 a (18 buildings) calculated with national primary energy factors: 1.0 for natural gas, 0.65 for district heating, and 2.0 for electricity
	Renewable energy export, $kWh/(m^2$ a)	Metered monthly values, updated annually	To be specified locally	< 1 kWh/m^2 a
	Carbon offset, $tCO_2/(person \cdot a)$	Not in practice	To be specified locally	0 $tCO_2/(person \cdot a)$
	Carbon footprint of building materials for new construction and major renovation, $kgCO_2\text{-}eq/m^2$	Calculated value from the design documentation for the new construction research building (CON)	To be specified locally	5.86 kg CO_2eq/m^2 a

Within the same CCE indicator set, the calculated carbon footprint for indicator “carbon footprint of building materials from new construction and major renovation” amounts to 5.86 kg $CO_2eq/(m^2 \cdot a)$ based on the design documentation of the CON research building. This indicator alone involves several modules across different stages of building LCA and is further discussed in depth in a different case study with a much larger sample size in Section 3.4.2 of this thesis using the QCEPM model developed in Publication 3.

3.4.2 Embodied carbon results from QCEPM analysis

For the final indicator under the CCE category of PICSOU — Carbon footprint of building materials for new construction and major renovation, quantitative results are derived from application of the QCEPM developed in Publication 3 and introduced in Section 2.4.1 of this thesis.

We applied the data processing method described in thesis Section 2.4.1 to all 20 sets of data. This yielded the total quantities of concrete, rebar, and masonry used in each project. We then converted the quantities into carbon emissions, added up the total carbon emissions for each data set and calculated their respective carbon emissions per unit area, the results are listed in Table 11.

Table 11. Process carbon emissions data (in ascending order of gross area)

Data set #	Quantity Concrete (m^3)	 Rebar (t)	 Masonry (m^3)	Carbon emissions ($kgCO_2e$)	Gross area (m^2)	Carbon emissions/unit area ($kgCO_2e/m^2$)
1	1618.60	138.43	597.43	971114.28	2411.92	402.63
2	1259.19	168.43	643.17	977463.40	3054.08	320.05
3	2028.72	228.79	3925.88	2436649.78	4640.73	525.06
4	3797.81	187.73	918.32	1737206.39	4940.44	351.63
5	1897.44	168.73	1006.18	1289469.01	4964.08	259.76
6	2089.77	158.16	1285.66	1359164.66	5277.91	257.52
7	609.90	260.84	1172.56	1181110.56	5387.06	219.25
8	2192.10	214.19	780.68	1405111.38	5594.79	251.15
9	1715.64	211.94	1545.25	1442744.98	5775.11	249.82
10	2291.90	256.95	1384.37	1862171.38	5787.97	321.79
11	3026.36	294.37	1420.99	2053804.75	6075.29	338.06
12	3417.75	236.94	1790.69	2189107.89	6869.34	318.68
13	2756.31	230.94	1672.39	1923116.79	6995.58	274.90
14	3479.03	580.38	2020.19	3078582.56	7575.78	406.37
15	2560.02	295.90	1248.16	1768854.13	7960.50	222.20
16	2988.17	263.80	1391.80	1856599.36	8029.49	231.22
17	2735.34	412.73	1259.19	2194156.84	8051.75	272.51
18	2459.30	340.31	2161.22	2249875.76	8876.40	*253.48*
19	3266.15	447.05	1740.60	2604957.50	9009.63	*289.13*
20	3942.87	607.96	1123.67	2909373.28	9934.70	292.85

Using the 20 training datasets, the solved QCEPM regression model was expressed as:

$$E = 271.499C + 2470.192R + 348.319M \tag{37}$$

where E denotes total embodied carbon emissions, C the quantity of concrete, R the quantity of rebar, and M the quantity of masonry.

Multicollinearity among the QCEPM predictor variables was evaluated using variance inflation factor (VIF) criteria of 0 < VIF ≤ 5 (no multicollinearity), 5 < VIF ≤ 10 (weak multicollinearity), 10 < VIF ≤ 100 (moderate–strong multicollinearity), and VIF > 100 (strong multicollinearity). Observed VIF values were 1.522 for concrete, 1.557 for rebar, and 1.039 for masonry, with corresponding capacities of 0.657, 0.642, and 0.963, respectively (see Table 12).

Table 12. Collinearity analysis results

	Collinearity statistics	
	Capacity	VIF
Concrete	0.657	1.522
Rebar	0.642	1.557
Masonry	0.963	1.039

Analysis of variance (ANOVA) validation yielded an F-statistic of 666.835 with a significance of $p = 0.000 < 0.05$ (see Table 13). Variance partitioning showed between-group sum of squares of 6.8427×10^{12} with degrees of freedom (DOF) = 3, within-group sum of squares of 5.4728×10^{10} with DOF = 16, and a total sum of squares of 6.8975×10^{12} with DOF = 19.

Table 13. Analysis of variance results

	Sum of squares	**Degrees of freedom**	**Mean square**	**F-Value**	**Significance**
Between	6842727600158.907	3	2280909200052.969	666.835	0.000
Within	54728000956.385	16	3420500059.774	—	—
Total	6897455601115.293	19	—	—	—

Regression coefficient estimates were β_1 = 271.499 for concrete with a standard error of 19.154 ($p < 0.001$), β_2 = 2470.192 for rebar with a standard error of 126.637 ($p < 0.001$), and β_3 = 348.319 for masonry with a standard error of 19.021 ($p < 0.001$). The intercept was β_0 = −18,040.215 with a standard error of 7,026.180 and $p = 0.706 > 0.05$, and was therefore excluded from the final predictive formulation (see Table 14).

Table 14. Regression and T-test

	Unstandardized Coefficients		**Standardized coefficients**	**t**	**Significance**
	B	**Standard error (σ)**	**Beta**		
(Constant)	-18040.215	7026.180	—	-0.384	0.706
Concrete	271.499	19.154	0.389	14.175	<0.001
Rebar	2470.192	126.637	0.542	19.506	<0.001
Masonry	348.319	19.021	0.416	18.312	<0.001

Goodness-of-fit statistics for the final model were R = 0.996, R^2 = 0.992, and adjusted R^2 = 0.991, with a standard error of the estimate of 58485.04133 kg CO_2 and a Durbin–Watson statistic of 1.939 (see Table 15).

Table 15. Model fit degree and Durbin Watson test result

Model	R	R^2	Adjusted R square	Std. error of the estimate	Durbin-Watson
1	0.996	0.992	0.991	58485.04133	1.939

Internal validation across 20 datasets compared QCEPM-based embodied-carbon estimates with manually calculated values, yielding percentage errors within ±6.61 % (see Table 16 and Figure 28). The observed percentage errors ranged from −6.61 % to +6.22 %, and the corresponding mean absolute percentage error (MAPE) was 2.360 %, giving an overall predictive accuracy of 97.640 % for the internal dataset (see Figure 29).

Table 16. Error analysis between QCEPM calculation and manual calculation

Data Set #	Manual calculation ($kgCO_2$)	QCEPM calculation ($kgCO_2$)	Error (%)
1	971114.28	989493.1801	1.89
2	977463.40	981951.5956	0.46
3	2436649.78	2483409.275	1.92
4	1737206.39	1814699.065	4.46
5	1289469.01	1282420.17	-0.55
6	1359164.66	1405875.837	3.44
7	1181110.56	1218337.048	3.15
8	1405111.38	1396169.059	-0.64
9	1442744.98	1527567.243	5.88
10	1862171.38	1739166.767	-6.61
11	2053804.75	2043761.948	-0.49
12	2189107.89	2136934.35	-2.38
13	1923116.79	1901326.762	-1.13
14	3078582.56	3081873.76	0.11
15	1768854.13	1860730.526	6.22
16	1856599.36	1947712.201	4.91
17	2194156.84	2200764.22	0.30
18	2249875.76	2261122.519	0.50
19	2604957.50	2597339.844	-0.29
20	2909373.28	2963658.801	1.87

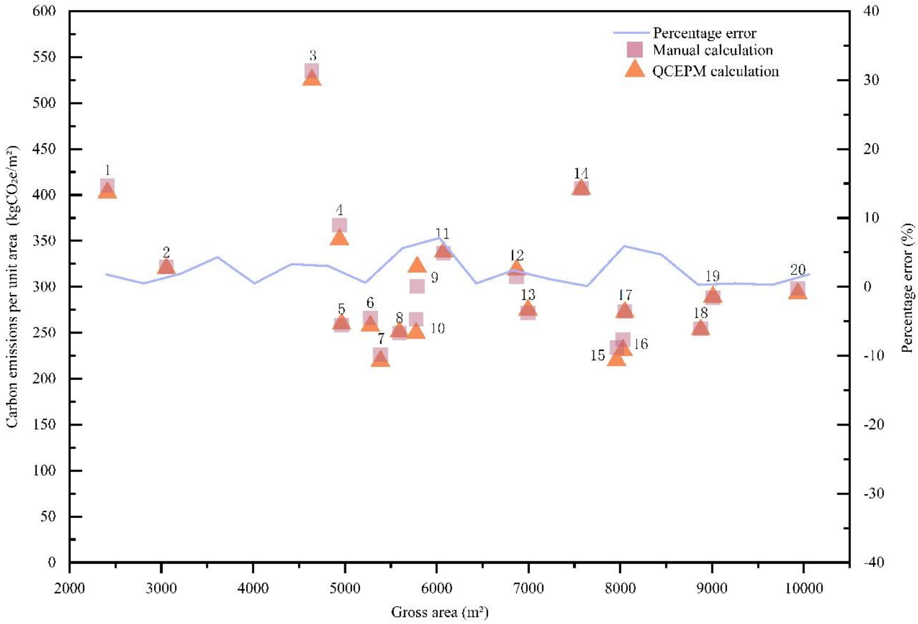


Figure 28. Distribution of 20 data sets in terms of specific carbon emissions ($kgCO_2/m^2$) and the percentage error (%) between their QCEPM-calculated and manually calculated results

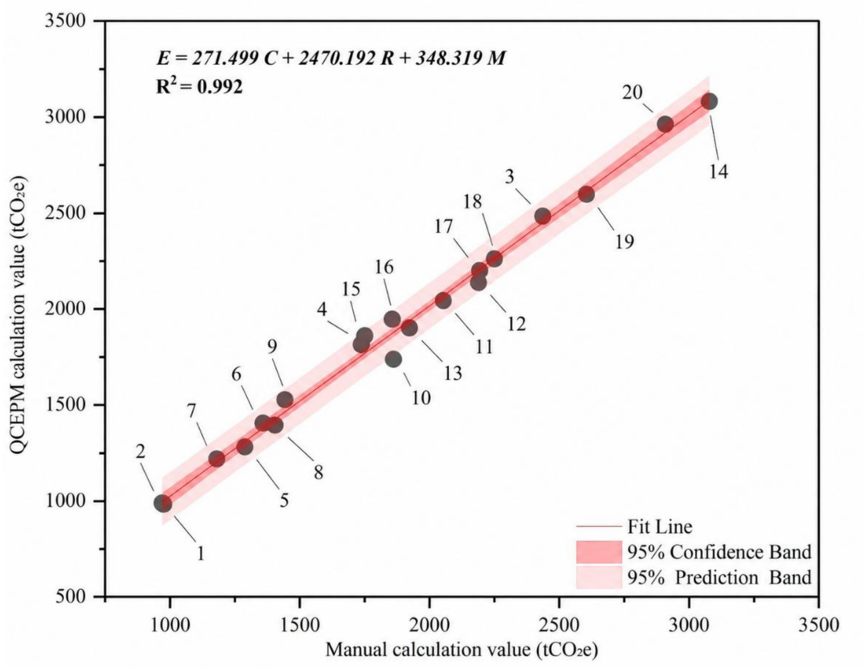


Figure 29. Correlation between QCEPM-calculated and manually calculated CO_2 values

External validation was conducted using 10 additional building projects located in Chengdu and Chongqing, with gross floor area ranging from 1861.31 m^2 to 18109.90 m^2 and completion years between 2022 and 2023 (see Table 17). For these case-study projects, comparison between QCEPM-based and manually calculated embodied-carbon values produced percentage errors from −0.86 % to +2.11 %, with unit-area errors ranging from −2.59 to +4.74 kg CO_2/m^2 (see Table 18). The maximum absolute percentage error reported for the 10 projects was 2.11 %, and the accumulative unit-area error across all projects was 7.87 kg CO_2/m^2, as shown in Figure 30 (Publication 3).

Table 17. Case project information

Data set #	Project name	City	Structure type	Gross area (m^2)	No. of floors	Year
1	Jinjiang Commercial Building	Chengdu	Framing	1861.31	2	2023
2	Longjianglu Elementary School building	Chengdu	Framing	3002.10	6	2023
3	Jinxiu Residence	Chengdu	Framing	4940.44	6	2023
4	Banan Middle School building	Chongqing	Framing	5277.91	5	2023
5	Liangchen Residence	Chengdu	Framing	5648.51	3	2022
6	Zuoyu Residence	Chengdu	Framing	8315.25	6	2023
7	Rilian Residence	Chengdu	Framing	8798.40	6	2023
8	Xiayu Residence	Chengdu	Framing	10264.80	7	2023
9	Aochuang Commercial Complex	Chengdu	Shear wall framing	13645.65	5	2022
10	Tianchen Office Tower	Chengdu	Framing	18109.90	6	2023

Table 18. Case study results (in ascending order of project gross area)

Data set #	Quantity Concrete (m^3)	Rebar (t)	Masonry (m^3)	Manual calculation ($kgCO_2$)	QCEPM calculation ($kgCO_2$)	Error (%)	Unit area error ($kgCO_2/m^2$)
1	716.42	98.11	600.42	642724.42	645995.54	0.51	1.76
2	1421.71	156.53	1106.59	1149602.60	1158098.32	0.74	2.83
3	2756.98	160.13	1104.71	1526345.96	1528860.64	0.16	0.51
4	1408.81	177.65	1121.72	1186995.56	1212036.50	2.11	4.74
5	2233.84	261.11	1097.11	1622969.47	1633621.42	0.66	1.86
6	2657.55	268.99	2318.96	2206884.00	2193716.94	-0.60	-1.58
7	3291.52	353.76	2425.03	2634963.66	2612183.54	-0.86	-2.59
8	2708.1	386.91	2739.7	2649052.36	2645277.99	-0.14	-0.37
9	4518.09	769.52	1405.15	3610613.97	3616959.51	0.18	0.46
10	4565.1	665.99	3741.03	4183085.05	4187615.08	0.11	0.25

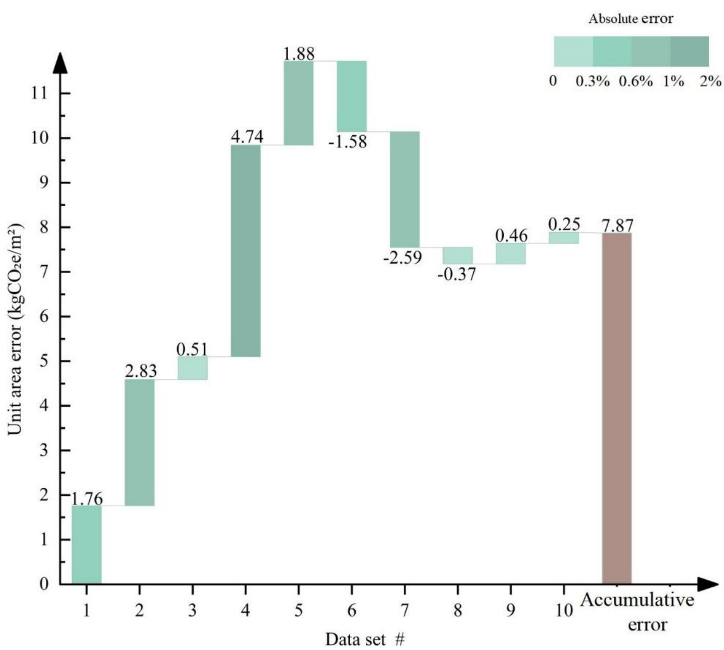


Figure 30. Accumulative unit area error of 10 case study projects

3.5 Transportation

3.5.1 Survey-based commuting emissions

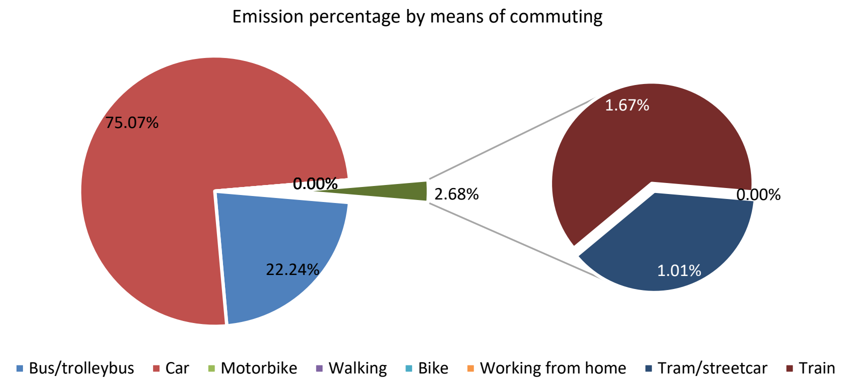
Survey-based commuting emissions for TalTech's Mustamäe Campus were estimated by applying Tallinn city commuting-mode percentage distributions derived from an online survey [52] to the campus commuting population of 11226 persons, following the population-scaling procedure described in Publication 2. Carbon emissions were calculated using Equation (35) and Equation (36) defined in Section 2.5.1 of the thesis. Based on the baseline dataset reported in Publication 1, the resulting total annual commuting carbon footprint for the campus was 3975 tCO_2 in year 2022.

3.5.2 Mode-wise contribution to total commuting carbon footprint

Mode-wise decomposition of commuting emissions was derived from the baseline dataset reported in Publication 1 (see Table 19). Of the 11226 total commuters (Mustamäe campus' total university population as of year 2022), car travel accounted for 31.82 % (3572 persons) and generated 2984.3 tCO_2, while bus/trolleybus transport represented 36.36 % (4082 persons) with 884.1 tCO_2. Non-motorized travel modes comprised 21.59 % walking (2424 persons; 0 tCO_2) and 4.55 % biking (511 persons; 0 tCO_2) and working from home represented 2.27 % (255 persons; 0 tCO_2). Additional motorized contributions originated from tram/streetcar travel at 2.27 % (255 persons; 40.1 tCO_2) and train travel at 1.14 % (128 persons; 66.6 tCO_2).

Table 19. Overview of TalTech Mustamäe campus' commuting CO_2 emissions

Means of commuting	Percentage %	Calculation assumptions	Number of commuters	Annual CO2 emissions tCO2
Bus/trolley bus	36.36	20g of CO2 per minute for each passenger, daily one-way commuting time is 21.66 min, 250 working days annually	4082	884.1
Car	31.82	132.4g of CO2 per km, daily one-way commuting distance is 12.62km, 250 working days annually	3572	2984.3
Motorbike	0	80g of CO2 per minute, 250 working days annually	N/A	N/A
Walking	21.59	N/A	2424	0
Bike	4.55	N/A	511	0
Working from home	2.27	N/A	255	0
Tram/streetcar	2.27	15g of CO2 per minute for each passenger, daily one-way commuting time is 21 min, 250 working days annually	255	40.1
Train	1.14	10g of CO2 per minute for each passenger, daily one-way commuting time is 104 min, 250 working days annually	128	66.6
Overview ⬇		**Total ➡**	**11226**	**3975**



3.5.3 Novel workflow-based commuting emissions

Novel workflow-derived commuting emissions were quantified using datasets from Telia Crowd Insight (TCI) [53] and Fyma [54], with all calculations documented in the TalTech 2022 greenhouse gas inventory [55]. Filtered Telia datasets provided total annual travel distances for the commuting population, classified into private car, public transport (mode unspecified), and walking categories. Because Telia tracks all device movements in the surrounding area, these activity estimates were normalized using Fyma camera observations to separate campus-related commuter flows from pass-by movements.

Novel workflow-derived activity totals included 11,760,009 passenger-km by car and 4,204,780 passenger-km by public transport. Application of the novel workflow produced a commuting carbon footprint of 1444 tCO_2 (see Table 20).

Table 20. Overview of TalTech Mustamäe campus' commuting emissions in year 2022 based on the novel workflow (Publication 2)

Means of commuting	Annual activity data	Unit	Emission factor	Unit	Annual emissions, tCO2
Passenger car	11760009	passenger-km	0.149	kgCO2e/passenger -km	1414
General public transportation	4204780	passenger-km	0.009	kgCO2e/passenger -km	30
Two-wheeled vehicles	3294696	km	0	kgCO2e/km	0
Walking	364687	km	0	kgCO2e/km	0
		Total ➡			1444

3.5.4 Comparison of results from conventional and novel workflows

Comparison across the conventional and novel commuting-emission calculation workflows was conducted using the emission values reported in Publication 2. The conventional workflow produced a total annual commuting carbon footprint of 3975 tCO_2, whereas the novel workflow (Telia Crowd Insight combined with Fyma normalization) yielded 1444 tCO_2. Two additional values were generated through validation of the TCI+Fyma datasets: an unnormalized Telia-only estimate of 3046.9 tCO_2 and a normalized value of 1218.8 tCO_2 using a single Fyma factor of 0.4 (see Table 21).

Quantitative differences reported in Publication 2 describe the relative magnitudes among these results (see Table 22). The conventional workflow result was 175% greater than the TCI+Fyma result, while conventional workflow's result exceeded the unnormalized validation value by 30.5%. Differences between the TCI+Fyma result and the normalized validation result were comparatively smaller, with the former estimate being 18.5% higher (Publication 2).

Table 21. Differences between the results obtained using the conventional approach, the novel approach, and the arithmetic validation of the novel approach

Approach	Practice	Data attribute	Critical metrics	Emissions, tCO_2
Conventional	The PICSOU framework	Publicly available data: fully based on existing survey statistics	Total annual travel distance (km): 22540034.3 by car; Total annual travel time (min): 44205608 by bus; 2675717 by tram; 6654773 by train	3975
Novel	TalTech 2022 GHG Inventory	Sampled and filtered Telia Crowd Insight data normalized by month-specific Fyma factors derived from camera footages	Total annual passenger-km: 11760009 by car; 4204780 by public transport	1444
	Data validation	Sampled and filtered Telia Crowd Insight data normalized by a single weighted average Fyma factor of 0.4 derived from camera footages	Total annual travel distance (km): 39505192.5 from all modes of traveling including walking and biking	Unnormalized: 3046.9 Normalized: 1218.8

Table 22. Comparison of emission values measured using different methods, percentage difference calculated using the same equation: [(bigger value - smaller value)/smaller value]*100%, only relevant percentages were calculated.

	PICSOU 3975 t	Inventory (TCI + Fyma) 1444 t	Validation (unnormalized) 3046.9 t	Validation (normalized) 1218.8 t
PICSOU: 3975 t	0%	175%	30.50%	-
Inventory (TCI + Fyma): 1444 t	-	0%	-	18.50%

4 Discussion

Chapter 4 examines the implications of the quantitative results reported in Chapter 3 for campus planning and operational decision-making within the PICSOU framework. The discussion focuses on how the observed performance patterns in each category: efficiency and learning environment, IEQ, CCE, and transportation to inform the practical adjustments that can be supported by measured evidence. Unlike Chapter 3, which reports category-level outcomes without interpretation, this chapter evaluates how the documented deviations from benchmark values constrain or enable changes in space allocation, IEQ strategies, carbon-management workflows, and mobility planning. Each subsection develops an analytical link between the empirical results and the decision pathways they substantiate, while remaining within the evidential and methodological limits defined by the appended publications.

4.1 On space efficiency and learning environment

4.1.1 Room utilization patterns

The findings in Publication 1 indicate that the utilization characteristics of classrooms in the U03 reference building diverge substantially from the operational benchmarks defined under the space-efficiency category. The utilization metric applied in Publication 1 is based on booking frequency relative to a 42.5-hour academic week and occupancy relative to nominal capacity, as formalized in Equation (1), from which, Publication 1 reports utilization values ranging from approximately 10% to 43%, with a building-level mean of 29%, compared against the target utilization of 56%. The associated per-student area of 1.41 m^2 also falls below the benchmark range of 1.5–2.0 m^2 plus 5 m^2 allocated for presentation activities (see

Table **23**). These numerical comparisons collectively establish a systematic deviation between measured and expected space-use levels.

Table 23. Overview of TalTech Mustamäe campus' target and baseline values for space efficiency

PICSOU category	Key performance indicators (KPIs)	Data source/update frequency	Target value	TalTech baseline value (result from case study)
1. Space efficiency & learning environment	Auditoriums and other learning spaces measured by m^2 per student	Calculated from campus summary form, updated annually	1.5-2.0 m^2 + 5 m^2 for presentation can be even bigger range, 75% occupancy rate, 56% utilization	1.41 m^2, presentation area usually bigger than 5 m^2, occupancy rate by default is 75%, average utilization rate per classroom/auditorium according to results from U03 building is 29% (U03)
	Teaching laboratory m^2 per student	Calculated from campus summary form, updated annually	4.0-6.0 m^2, 75% occupancy, 38% utilization (for teaching laboratories)	1.76 m^2 (considering all types of laboratories), unable to document actual occupancy and utilization rate of laboratories (18 buildings)
	Office & meeting rooms per staff	Calculated from campus summary form, updated annually	12 m^2	13.4 m^2 (18 buildings)
	Total space per person (staff + students)	Calculated from campus summary form, updated annually	To be specified locally	10.3 m^2 (18 buildings)
	Self-learning and group working spaces (informal learning seats), number of informal seats per formal seat	Calculated from campus summary form, updated annually	0.3 informal learning seats to every formal seat	0.50 m^2 per student, this result only accounts for documented self-learning spaces, informal learning spaces are not documented. Number of informal learning seats is not possible to document, nor is its portion to formal learning seats. (18 buildings)
	Sports facility per person (staff + students)	Calculated from campus summary form, updated annually	To be specified locally	1.12 m^2 (18 buildings)

4.1.2 Implications for space allocation and scheduling

Publication 1 further notes that utilization near 10% coexists with U03's maximum of 43%, indicating substantial intra-building variation in booking intensity. This distributional pattern, likely can be expected from other buildings with comparable layouts and functions, suggesting that the identified under-utilization is not confined to the U03 building.

The implications outlined in Publication 1 link these utilization outcomes directly to campus-planning considerations. The documented under-utilization contradicts the prevailing assumption that new premises are needed to support increased teaching or research activity. Instead, such measured capacity slack suggests an opportunity to reduce operational emissions and costs through redistribution of existing space rather than through expansion. This interpretation aligns with the space-efficiency improvement strategies, which include: (1) increasing the area of over-utilized spaces; (2) reducing or converting under-utilized spaces; (3) rearranging internal layouts; (4) releasing unnecessary spaces; and (5) creating new spaces only when supported by empirical justification (see Table 24).

Table 24. Qualitative cost-benefit breakdown of improvement measures for space efficiency at TalTech's Mustamäe campus

PICSOU category	Improvement measure	Applicability	Cost category	Benefit category
1. Space efficiency & learning environment	1. Increase area of over-utilized spaces	generic	Renovation cost, Remodeling cost, Lease cost, Construction cost	Improved learning performance, Increased productivity, Improved wellbeing
	2. Reduce area of/convert under-utilized spaces	building-specific		
	3. Rearrangement of spaces	generic		
	4. Release unnecessary spaces	generic		
	5. Create new spaces if proven necessary	generic		

However, the current KPI set for the space efficiency and learning environment category may be non-conclusive and requires further development. This limitation pertains specifically to the interpretability of utilization results within this PICSOU category as the numerical indicators mostly quantify capacity use. Within this constraint, the current findings only support the use of utilization mapping as a diagnostic tool for identifying inefficiencies in space allocation and for guiding resource-optimization decisions within the PICSOU framework, but do not independently characterize learning-environment quality (Publication 1).

4.1.3 Parking space efficiency

The results in Section 3.2.4 of the thesis show that the parking target derived from the LEED-referenced workflow (see Figure 4) for this indicator is 0.05 spaces per person, while Publication 1 reports an existing provision of 0.10 spaces per person and a required 43.5% reduction in parking footprint to reach the reference level. This deviation indicates that current parking allocation does not align with the optimized benchmark adopted for the space-efficiency category.

Such benchmark misalignment corresponds to both spatial and environmental implications. Reducing the parking footprint is presented as a means to minimize land consumption, automobile dependence, car-related emissions, and less intuitively, rainwater runoff – because parking areas are predominantly hardened surfaces with low infiltration capacity, a smaller parking footprint reduces the extent of impervious ground area and thereby decreases runoff. Within the space-efficiency category, deviation from reference values is treated as an indicator of relocatable or reducible area, and parking therefore falls under the same adjustment logic as other campus spaces that exceed their reference allocations, with potential measures including releasing unnecessary areas, converting over-allocated space, and rearranging spatial assignments (Publication 1).

4.2 On IEQ

4.2.1 Reliability of diagnostic IEQ parameters

The reliability of diagnostic IEQ parameters is quantitatively assessed through a cross-validation of occupancy detection methods. This assessment began with an initial verification of the FMCW radar module itself, which confirmed a positive correlation between its occupancy data and average CO_2 concentrations across most space types, thereby validating the module's fundamental operational reliability. Anomalous behavior in dormitories, where duration curves for 83% and 67% occupancy probabilities overlapped, was attributed to increased natural ventilation in small spaces, further confirming the realism and accuracy of the FMCW-derived data as described in Section 3.3.3 of this thesis (see Figure 19).

Building on this verified baseline, the cross-campus verification using CDJCC's 26,077 data rows converted to TalTech rule-based occupancy model (a room is classified as "occupied" if the indoor CO_2 concentration remains above 550 ppm over a 10-min interval, and the resulting binary occupancy status is inferred solely from the CO_2 time series without using any FMCW radar information) shows an overall matching ratio of 0.611 between the CO_2-based inference method at TalTech and direct FMCW radar detection at CDJCC (see Table 25 and Figure 31). This agreement is highly phase-dependent: the matching ratio rises to 0.758 during CO_2 growth phases but falls to 0.479 during decay phases. The spring semester data (18,396 rows) showed a ratio of 0.608, with a high match of 0.752 in growth phases and a low of 0.473 in decay phases. The autumn data (7,681 rows) showed a slightly higher overall ratio of 0.62. This discrepancy confirms that the CO_2-based proxy is less specific and reliable (due to its conservative numerical-rule-based nature) than the independently verified radar-based detection, particularly during non-monotonic CO_2 changes, leading to a satisfactory comparability, but also visibly uneven reliability of occupancy-informed IEQ parameters across campuses (Publication 5).

Table 25. Cross-validation of TalTech's CO2-based occupancy inference using CDJCC's FMCW-based occupancy detection results (converted to TalTech rule-based occupancy model)

Metric	Spring-semester dataset	Autumn-semester dataset	Spring + Autumn combined
Number of rows with CO_2-based occupancy prediction	18,396	7,681	26,077
Fraction of predicted rows in growing phase	0.483	0.449	0.473
Fraction of predicted rows in decaying phase	0.517	0.551	0.527
Number of matching rows (prediction = FMCW)	11,177	4,765	15,942
Matching ratio	0.608	0.62	0.611
Matching in growth phase	0.752	0.776	0.758
Matching in decay phase	0.473	0.494	0.479

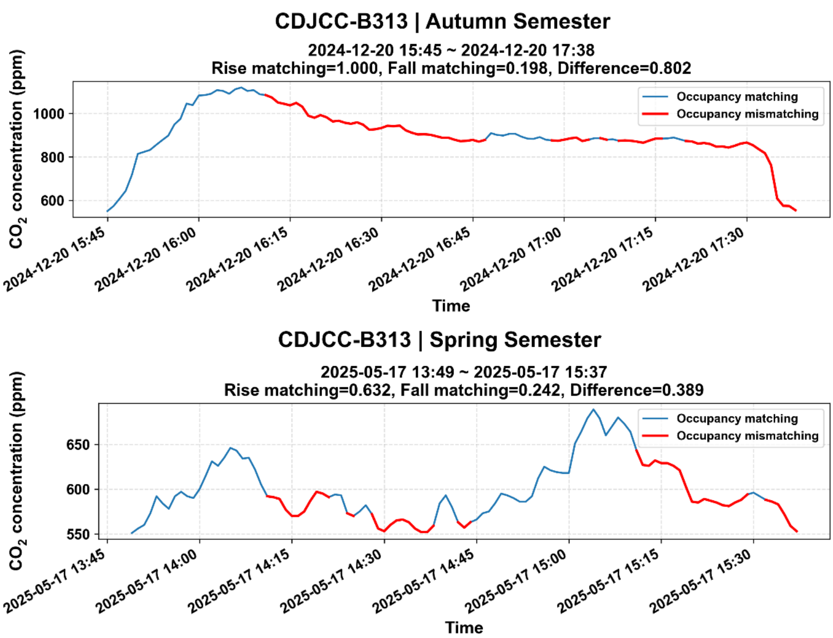


Figure 31. Representative CO2 concentration cycles used to illustrate the methodological comparability between CDJCC's FMCW radar-based and TalTech's CO2-based occupancy detection.

4.2.2 Conditional evaluation workflow

Publication 5 defines λ_{season} and I/O as empirical indicators and evaluates their consistency using monitoring data under the conditional evaluation workflow (see Figure 32).

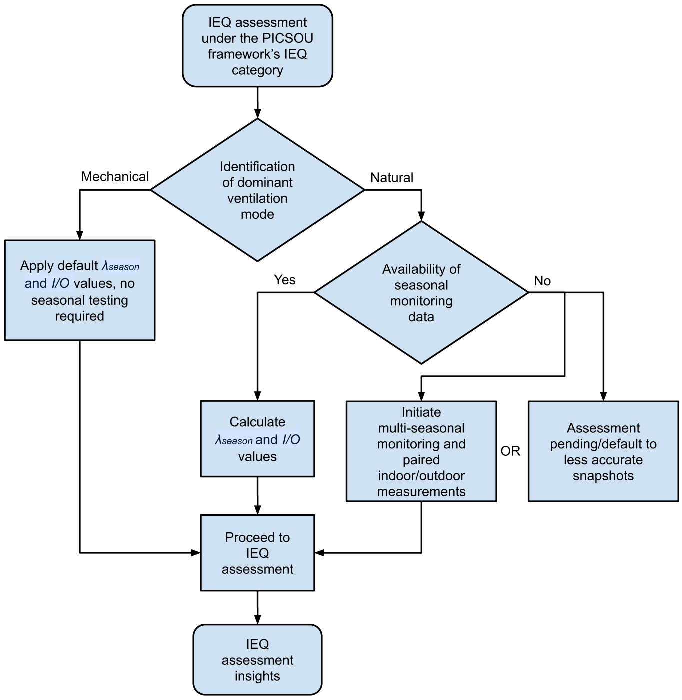


Figure 32. Decision workflow for climate-resilient IEQ assessment under the PICSOU framework

λ_{season} is defined by Equation (38) below as the ratio of autumn to spring indoor CO_2 averages under comparable occupancy, with $\lambda_{season} > 1$ indicating weaker effective ventilation in autumn and $\lambda_{season} \approx 1$ indicating limited seasonal contrast.

$$\lambda_{\text{season}} = \frac{\overline{\text{CO}_2}_{\text{Autumn}}}{\overline{\text{CO}_2}_{\text{Spring}}} \tag{38}$$

I/O is defined by Equation (39) below as the ratio of seasonal indoor to outdoor $PM_{2.5}$ averages from paired indoor–outdoor measurements, with values near 1, well below 1, or above 1 corresponding respectively to high coupling, attenuation, or indoor sources or data issues.

$$\text{I/O} = \frac{\overline{PM_{2.5}}_{\text{Autumn}}}{\overline{PM_{2.5}}_{\text{Spring}}} \tag{39}$$

Room-level λ_{season} and I/O values are computed and grouped by campus, semester, and space type. For each group, Publication 5 reports the number of rooms, the mean indicator value, the standard deviation, and the 95 % confidence interval based on a t-distribution, treating rooms as independent observational units. These confidence intervals serve as empirical consistency checks for the indicators rather than as derivation steps. Comparative patterns in Table 26 and Table 27 across CDJCC and TalTech, and across dormitories, classrooms, and offices, are used to verify that λ_{season} and I/O behave in accordance with their conceptual definitions under the available monitoring sample.

Table 26. T-distribution-based 95% confidence interval test results for λ_{season} using the CDJCC and TalTech CO2 datasets as examples

Campus	Group	N	Mean	SD	CI95_low	CI95_high
CDJCC	classrooms	4	0.8497	0.1136	0.6689	1.0305
	dorms	6	0.7874	0.2629	0.5115	1.0634
	offices	2	0.9387	0.0210	0.7503	1.1270
	outdoors	2	0.8496	0.0005	0.8447	0.8545
CDJCC	indoor	12	0.8334	0.1956	0.7091	0.9577
TalTech	classrooms	6	1.0988	0.1021	0.9916	1.2059
	office	3	1.0407	0.0229	0.9839	1.0976
	outdoors	2	1.0307	0.0042	0.9931	1.0684
TalTech	indoor	9	1.0794	0.0866	1.0129	1.1460

For λ_{season}, the CDJCC indoor mean of 0.8334 (CI 0.7091–0.9577) contrasts with the TalTech indoor mean of 1.0794 (CI 1.0129–1.1460), and this campus-level separation is preserved across room types, with CDJCC classroom, dormitory, and office means between 0.7874 and 0.9387, and TalTech means between 1.0407 and 1.0988. These ranges indicate that the seasonal contrast captured by λ_{season} is stable at both the room-type and campus levels, even with sample sizes as low as N = 2–6 per group.

Table 27. T-distribution-based 95% confidence interval test results for I/O ratio using the CDJCC and TalTech $PM_{2.5}$ datasets as examples

Campus	Season	Group	N	Mean	SD	CI95_Low	CI95_High
CDJCC	spring semester	classrooms	4	1.0543	0.0519	0.9717	1.1369
		dorms	6	0.8737	0.0978	0.7711	0.9763
		offices	2	0.9942	0.032	0.7069	1.2815
		all	12	0.954	0.1124	0.8826	1.0254
	autumn semester	classrooms	4	0.9496	0.0592	0.8554	1.0438
		dorms	6	0.7997	0.091	0.7043	0.8952
		offices	2	0.7743	0.0267	0.5343	1.1043
		all	12	0.8454	0.1039	0.7794	0.9114
	spring and autumn semester		24	0.8997	0.1195	0.8493	0.9502
TalTech	spring semester	classrooms	6	0.3532	0.3869	−0.0528	0.7593
		office	3	0.379	0.3018	−0.3708	1.1287
		all	9	0.3618	0.3413	0.0994	0.6242
	autumn semester	classrooms	7	0.1681	0.0981	0.0774	0.2589
		office	4	0.2244	0.073	0.1082	0.3406
		all	11	0.1886	0.0905	0.1278	0.2494
	spring and autumn semester		20	0.2665	0.2474	0.1508	0.3823

For the I/O ratio, CDJCC room-type means remain near or moderately below unity in spring (1.0543, 0.8737, 0.9942) and shift downward in autumn (0.9496, 0.7997, 0.7743), while TalTech means remain substantially below unity in both semesters, including 0.3618 (spring-all) and 0.1886 (autumn-all).

The ”CI95_High” column in Table 27, which corresponds to its counterpart reported in Table 6 in Publication 5, has been recalculated as a copy-and-paste transcription error was found in some reported 95% CIs. This thesis features the corrected 95% CI entries based on the original calculations. This correction does not affect the underlying data, statistical analyses, interpretation of results, or the main conclusions.

These distributions, together with the associated 95% confidence intervals, show that both indicators maintain directional consistency despite varying group sizes and variance levels. As a result, both λ_{season} and I/O provide a stable basis for conditioning the interpretation of IEQ measurements, ensuring that differences arising from seasonal ventilation behavior and indoor–outdoor particle coupling are accounted for before higher-level comparative assessments are made.

4.2.3 Case studies’ contribution to IEQ indicator development of PICSOU

Publication 1 introduces the initial IEQ indicators in the PICSOU framework by identifying the percentages of number of rooms belonging to each indoor air quality and thermal comfort category (see Table 8). Reference building U03’s results show that the initial IEQ indicators can distinguish between rooms that meet the target categories and those do not, but cannot identify any underlying correlation or patterns.

Publication 5 introduces occupancy-coupled CO_2, $PM_{2.5}$ and temperature measurement for CDJCC and TalTech and adds nuanced compliance threshold information unspecified in Publication 1. The monitored results show that CO_2 compliance issues, where present, are restricted to specific space types and seasons, whereas $PM_{2.5}$ compliance varies systematically across campuses and seasons, with clear contrasts between the two climate zones. Temperature compliance also shows distinct patterns across space types and seasons at both campuses. These compliance trends demonstrate that each IEQ parameter follows its own spatial and seasonal distribution and that the patterns differ between the two climate contexts represented by CDJCC and TalTech (see Table 9).

Together, the two case studies contribute to the development of the PICSOU IEQ category by demonstrating the limitations of relying solely on room-level category-compliance proportions and by showing that the drivers of IEQ compliance differ across parameters, space types, seasons and climate zones. Publication 1 contributes to the initial structure of the IEQ category, while Publication 5 contributes to parameter-specific compliance evidence and cross-context variation. The combined results confirms and emphasizes that a universally applicable PICSOU IEQ category should mandate explicit IEQ indicators such as CO_2, $PM_{2.5}$ and temperature, as well as the capacity to represent spatial (space type variation, indoor/outdoor difference), seasonal and climatic differences in compliance using climate resilient indicators such as seasonal ventilation coefficient λ_{season} and infiltration factor I/O.

4.2.4 IEQ co-benefits in retrofit economics

The breakdown of the annual unit area saving after energy efficiency retrofit featured in Figure 18 shows that saving from productivity increase due to improved IEQ contributes remarkably greater than energy saving. The retrofit corresponds to deep renovation recommended in Estonia's long-term renovation strategy [62] with a unit area cost of 600 €/m2, substituting this value together with the post-retrofit annual unit area benefit into Equation (16) yields a simple payback time of 39 years, a more favorable payback time compared to an 86-year simple payback time considering only energy saving.

The drastic reduction in simple payback time contributed by IEQ co-benefits is also given proof by the MAC value of -1160 €/(t CO_2eq · m^2) obtained in Section 3.3.2 of the thesis, its negative value indicates net savings rather than costs, which plays at building owners' long term financial favor, thus encouraging their investment in carbon footprint reduction. Such result further emphasizes the undeniable impact of IEQ co-benefits awareness over any environmentally conscious but budget-sensitive retrofit decision.

4.3 On CCE

4.3.1 Operational carbon footprint patterns

The CCE indicators in Publication 1 report a baseline carbon footprint of 1.30 tCO_2/(person · a) for the Mustamäe campus, based on metered electricity and heating data from 18 buildings. The same dataset yields electricity use of 1045 kWh/(person · a), heating use of 1265 kWh/(person · a), specific electricity use of 115 kWh/m² a, specific heating use of 176 kWh/m² a, and primary energy use of 349 kWh/(m² · a) using national primary energy factors of 1.0, 0.65, and 2.0, this implies a difference of 58 kWh/(m² · a) between delivered and primary energy. Renewable energy export is < 1 kWh/m² a, and carbon offset is 0 tCO_2/(person · a). The embodied-carbon indicator for new construction and major renovation based on the design documentation of the CON research building is 5.86 kg CO_2eq/(m² · a) (see Table 10).

Publication 1 reports total annual carbon emissions of 10626 t CO_2eq/a under these baseline conditions, together with annual energy cost of 2498480 EUR/a. Under the optimal-value scenario defined in Publication 1, where all buildings are heated by district heating and the lowest building-specific heating and energy-use values are applied to all buildings, annual carbon emissions are 3353 t CO_2eq/a, and annual energy cost is 754501 EUR/a. The arithmetic differences between baseline and optimal values are 7273 t CO_2eq/a for carbon emissions and 1743979 EUR/a for energy cost. The percentage differences are 68.4 % and 69.8 %, respectively (see Table 28). Expressed as ratios, baseline emissions are approximately 3.17 times the optimal value and baseline energy cost is approximately 3.31 times the optimal value. These ratios describe a sizable magnitude of change between the two calculation scenarios (baseline vs. optimal) defined in Publication 1.

Table 28. Carbon footprint/cost of PICSOU's CCE category calculated from TalTech Mustamäe campus' baseline values and optimal values

PICSOU category	Carbon footprint/cost based on baseline values	Carbon footprint/cost based on optimal values	Impact
3. Climate change & energy	Assumption: Actual situation in all buildings. Total energy cost: 2498480 EUR/a; Carbon footprint: 10626 tCO_2eq/a.	Assumptions: 1. All buildings heated by district heating; 2. Post-renovation energy saving and carbon footprint reduction apply to all buildings; 3. Specific heating/energy use across all buildings based on lowest real-life value. Total energy cost: 754501 EUR/a; Carbon footprint: 3353 tCO_2eq/a.	Annual energy saving by 1743979 EUR (69.8%); Annual carbon footprint reduction by 7273 tons (68.4%).

These differences result from variation in the underlying metered dataset, which specifies that buildings with lower measured heating and electricity use values set the reference values used in the optimal scenario. The resulting emission and cost differences therefore correspond to applying these lower measured values uniformly across the same set of 18 buildings.

Publication 1 lists CCE-related qualitative improvement measures in Table 29, these measures correspond to the same operational indicators reported in the CCE KPI set listed in Table 10.

Table 29. Qualitative cost-benefit breakdown of improvement measures TalTech's Mustamäe campus based on PICSOU's CCE category

Sustainability category	Improvement measure	Applicability	Cost category	Benefit category
Climate change & energy	1. Install passive/active solar systems	generic	Retrofit investment, Renewable energy certificate (REC) procurement cost, Material cost, Carbon offset investment	Reduced carbon footprint, Reduced energy cost, Improved energy efficiency, Minimized solid waste and pollution
	2. Use/produce green energy	generic		
	3. Eliminate refrigerants or use low-impact refrigerants	generic		
	4. Energy renovation (combined with IEQ improvement)	building-specific		
	5. Establish target value of building materials' carbon footprint for new build design and procure construction materials meeting recognized disclosure criteria such as ISO 14025 and EN 15804	generic		

The numerical evidence from Publication 1 therefore identifies the operational carbon footprint as the sum of metered electricity and heating use converted with the stated national primary energy factors and emission factors, with no contribution from carbon offsetting and < 1 kWh/(m² · a) renewable export. The difference between baseline and optimal values is defined entirely by substituting the lowest observed building-specific energy-use values into the same calculation structure. The individually calculated embodied-carbon indicator of 5.86 kg CO_2eq/(m² · a) from the CON research building is numerically smaller than the operational values but does not affect the operational calculations reported in Publication 1.

4.3.2 Embodied carbon footprint modeling

All discussions presented in this section are based on the QCEPM results from Section 3.4.2 of this thesis, contributing exclusively to the "carbon footprint of building materials for new construction and major renovation" indicator under PICSOU's CCE category.

For defining the distribution of the dependent variable, Table 11 presents the carbon-emission quantities associated with the construction-process stages used in model development. Publication 3 reports that these values determine the numerical range of the model's output space and establish the magnitude within which the regression analysis in Table 12, Table 13, Table 14 and Table 15 is conducted.

For assessing multicollinearity among the independent variables, Table 12 reports the variance inflation factors, whose interpretation is elaborated in Section 3.4.2 of this thesis. Publication 3 reports that all VIF values fall below 10 and therefore do not indicate correlation levels that would alter coefficient estimation. Publication 3 further states that under these VIF conditions, model construction using concrete, rebar and masonry does not introduce estimation bias or reduce estimation accuracy.

For evaluating model significance, Table 13 provides the ANOVA results. Publication 3 reports an F-value of 666.835 with corresponding significance = 0, which is below the 0.05 threshold and therefore meets the stated significance criterion. Publication 3 specifies that independent variables with significance < 0.05 are retained and variables with significance > 0.05 are removed. Table 14 lists the regression coefficients and their significance values. Publication 3 reports that concrete (β_1 = 271.499, σ = 19.154, significance < 0.001), rebar (β_2 = 2470.192, σ = 0.542, significance < 0.001), and masonry (β_3 = 348.319, σ = 0.416, significance < 0.001) satisfy the retention condition, while the constant term (β_0 = –18040.215, σ = 7026.180, significance = 0.706) exceeds 0.05 and is therefore not statistically significant according to the rule stated in Publication 3.

For assessing overall model fit and residual behavior, Table 15 presents the coefficient of determination and the Durbin–Watson statistic. Publication 3 reports an R^2 value of 0.991, indicating that 99.1% of the variance in the dependent variable is accounted for by the quantities of concrete, rebar and masonry. Publication 3 also reports a Durbin–Watson value close to 2.0 and uses this value to indicate the absence of autocorrelation in the residuals under the dataset evaluated further denoting a high level of truthfulness of QCEPM.

For quantifying model deviation from manual calculations, Table 16 provides error comparison across 20 datasets. Publication 3 reports that the difference between QCEPM-calculated and manually calculated values lies within ±6.61%. Publication 3 further reports a MAPE calculation using Equation (40):

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{40}$$

In which, $\hat{y} = \{\hat{y}1, \hat{y}2, \ldots, \hat{y}n\}$ represents the QCEPM calculation value and $y = \{y1, y2, \ldots, yn\}$ the manual calculation value. The MAPE calculation returned a value of 2.360%, corresponding to an accuracy of 97.640% for the datasets used.

For verifying model behavior on case-study projects, Table 17 and Table 18 present the input quantities and corresponding embodied-carbon values for 10 projects. Publication 3 reports that the maximum difference between QCEPM-calculated and manually calculated values across these projects does not exceed 2.11%, and that the accumulated unit-area difference is 7.87 kg CO_2eq/m^2.

Taken together, the study in Publication 3 defines QCEPM as a quantity-based regulatory model for estimating embodied carbon emissions in the A1–A5 (excluding A4) stages of the LCA of multi-story concrete frame structures – the dominant construction form in the Chinese building sector, as statistics from the National Bureau of Statistics of China indicates that, of the 8.76 billion m^2 total area under construction as of Q4 2024, reinforced concrete structures accounted for over 85% [63]. The quantities of concrete, rebar and masonry are stated to be available across construction-drawing budgeting, contract pricing, completion settlement and final accounts, enabling direct calculation of emissions. In other words, QCEPM works as a powerful and practical numerical tool for estimating the embodied carbon footprint of building materials for new construction, particularly those with multi-story reinforced concrete structure, the most adopted form of structure in markets whose building sector is featured by ultra-high construction volume and rapid physical expansion. Therefore, the proper utilization of QCEPM can directly address the first half of metrics specified by PICSOU Category 3's KPI 3.7 "carbon footprint of building materials for new construction and major renovation".

From a policy-making point of view, the study reports that these quantity-based values may be used with historical emissions data and regional carbon-peaking targets when forming regulatory schemes compatible with a standardized building sector carbon trading market. A carbon-trading workflow is described in which contract-pricing quantities define an emission limit and final-account quantities define actual emissions, with the difference determining credit purchases or sales. Quantity reporting during project execution is presented as a substitute for manual emissions monitoring. Such outputs can support regulatory policy design and enterprise decision-making.

4.4 On transportation

4.4.1 Inter-workflow comparison

Section 3.5.4 of the thesis compares the two transportation-emissions-measurement workflows by examining how their underlying data sources and processing assumptions lead to the differences reported in

Table 21. The conventional workflow is described as using publicly available commuting statistics with clearly documented mode-share assumptions. The novel workflow is based on Telia Crowd Insight and Fyma datasets whose intermediate processing steps are not disclosed. Because Telia's dataset does not identify specific commuting modes within public transport due to GDPR restrictions, the novel workflow cannot allocate emissions by mode in the same way as the conventional

workflow. This difference in identifiable transport-mode detail is considered one major reason the two workflows are not directly comparable.

For validating the data used by the novel approach, a validation calculation was performed using only Telia Crowd Insight data filtered by user-selected parameters. This validation workflow adopts a weighted-average Fyma normalization factor of 0.4, whereas the novel workflow uses month-specific Fyma factors produced by Fyma's data-processing procedures (Publication 2).

Table 22 presents the percentage differences used to quantify these effects. The difference between the conventional and novel workflows is 175%, the difference between the conventional workflow and the unnormalized validation result is 30.50%, and the difference between the novel workflow and the normalized validation result is 18.5%. The largest difference (conventional vs. novel) is due to the fact that the two workflows apply different activity boundaries: the conventional workflow allocates emissions by mode, whereas the novel workflow cannot distinguish individual modes within public transport. The smaller difference between the novel and normalized validation workflows arises from the use of different filtering and normalization choices applied to the same dataset, indicating that the data validation process for the novel approach approximated similar accumulative commuting activities as the novel approach did with its undisclosed algorithms. With such observation, it can be concluded that with the continued improvement in selection of data filters (as illustrated in Figure 33), the difference between commuting carbon footprint calculated using the novel approach and its normalized validation workflow is expected to be further reduced to an even more tolerable range below the current 18.5% disparity.

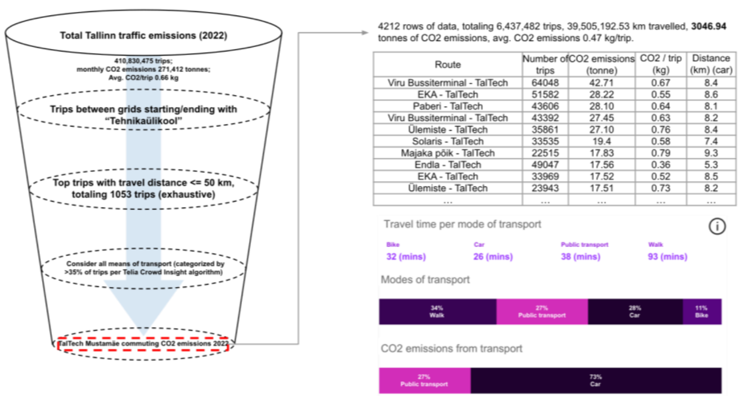


Figure 33. Data screening process and its resulting travel emissions insight produced on stand-alone Telia Crowd Insight data

Taken together, Publication 2 characterizes the novel workflow as primarily differing from the conventional one due to identifiable-mode detail, proprietary data-processing steps, GDPR-related aggregation of public-transport modes, and the normalization factors used. The numerical differences across workflows arise from structural features of the input data and processing rules rather than from inconsistencies in their respective calculation procedures.

4.4.2 Implications for campus mobility planning and policy

The study conducted in Publication 2 shows that commuting emissions auditing depends on the type of commuting information available in the entity's location. Entities in central areas can access commuting-mode distribution information more easily and can therefore apply a conventional workflow that allocates emissions to individual modes. Entities outside central areas may not have access to such statistics and can only document commuting emissions using a novel workflow that relies on mobility-data services when these services operate locally. This distinction defines whether emissions can be reported by mode or must remain aggregated.

The study reports 3975 tons of commuting carbon emissions using the conventional workflow and 1444 tons using the novel workflow. These two values arise from differences in data inputs rather than from computational steps. Because one workflow uses mode-share distributions and the other uses aggregated mobility data, each produces a different emissions value available for planning. Thus, the emissions figure used in decision-making is determined by the data that can be obtained at the entity's location.

The study also states that alternative data-collection approaches influence decision-making. Entities with access to commuting-mode statistics can evaluate changes to individual modes, while entities without such statistics must base decisions on aggregated emissions. The study further notes that normalization factors used with mobility data may require refinement, indicating that results produced through the novel workflow depend on the procedures applied by the data provider. These findings show that emission-aware commuting planning is determined by which data sources and levels of detail are accessible to the entity, and that workflow selection must be aligned with these data conditions.

4.5 Synthesis across framework categories

4.5.1 Intra and cross-category interactions within the PICSOU framework

Evidence from Chapters 2, 3 and 4 of the thesis shows that the PICSOU categories draw on common operational inputs. Several indicators documented in one category originate from the same operational variables that also determine results in other categories (see Table 30).

Space-use conditions influence IEQ and carbon outcomes: In Section 2.2.1, room utilization is defined from timetable-derived booking frequency and scheduled occupancy relative to room capacity, using institutional timetables and booking records as inputs. In Section 2.3.4, occupancy data is used to filter IEQ time-series so that IEQ performance is assessed specifically during occupied periods, with different occupancy-detection methods applied across campuses. In Section 3.3, CO_2 and temperature patterns follow room-use and occupancy behavior. In Section 3.4.1, operational indicators are derived from metered heating and electricity use and reported as unit-area and per-capita carbon indicators. In Section 4.1.2, utilization and scheduling patterns also affect how spaces function. These findings show that timetable-based utilization inputs and occupancy-filtered IEQ evaluation procedures establish a shared operational basis linking space-efficiency indicators, IEQ indicators, and operational CCE indicators.

IEQ results align with energy-use and cost patterns: In Section 2.3.8, IEQ improvement is evaluated through monetized productivity increase and monetized energy saving, and these terms are used together to quantify retrofit co-benefits. In Section 3.3, CO_2 and temperature patterns reflect ventilation behavior and occupancy. These same ventilation-related inputs also affect operational energy use reported in Section 3.4.1, where operational emissions are quantified from metered heating and electricity use and converted to unit-area and per-capita carbon indicators. In Section 4.2.4, IEQ co-benefits are evaluated together with carbon and cost effects. In Section 4.3.1, the CCE indicator set reports carbon footprint and energy cost outcomes under baseline and optimal scenarios. IEQ and CCE therefore respond to shared ventilation and thermal comfort inputs, and the thesis evaluates them within the same retrofit cost–carbon accounting logic.

Embodied carbon depends on the size and layout of building projects: In Section 2.4.1, the CCE indicator set includes the indicator “carbon footprint of building materials for new construction and major renovation,” and this thesis specifies its methodological scope within building life-cycle stages and modules as described and illustrated in Publication 5. In Section 3.4.1, the thesis explicitly notes that the embodied-carbon indicator for new construction and major renovation is discussed further using the QCEPM model in Section 3.4.2. In Section 3.4.2, embodied carbon is modelled from building material quantities. In Section 4.3.2, this modeling approach is interpreted in terms of its application logic for the embodied-carbon indicator under the CCE category. These links connect the CCE embodied-carbon indicator to space-planning variables through the dependence of material quantities on constructed areas and building specifications, without requiring the same building stock to be used for methodological contribution.

Transportation emissions depend on the commuting behavior of the same population used in other categories. In Section 2.5.1, the transportation indicator is defined as the carbon footprint from commuting trips measured per person, and the commuting population is defined as the sum of employees, students, and staff - same as ”university population”. In Section 2.5.2, the thesis defines two transportation workflows applied to the same campus boundary and time scope. In Section 3.5, transportation emissions are calculated based on commuting modes, and results are reported for conventional and novel workflows. In Section 4.4.1 and Section 4.4.2, workflow choice is interpreted in relation to commuting data availability for the defined commuting population. The same per-capita normalization logic is also used for operational CCE indicators in Section 3.4.1, where carbon indicators are reported per person. Transportation therefore interacts with categories that use per-person indicators through the shared population definition and shared per-capita reporting basis.

Table 30. Intra and cross-category interactions within the PICSOU framework

Primary indicator category	Interacting indicator category	Indicator-level linkage	Evidence sections referenced
Space efficiency and learning environment	IEQ	Learning-space utilization and scheduled occupancy determine when IEQ indicators (CO_2, temperature) are evaluated during occupied periods	Section 2.2.1 Space efficiency indicators; Section 2.3.4 Occupancy detection and inference; Section 3.2 IEQ
Space efficiency and learning environment	CCE (operational)	Total and heated building area derived from space provision affects operational energy use and per-capita operational carbon indicators	Section 3.3.1 Operational energy and carbon baseline at TalTech; Section 4.1.2 Implications for space allocation and scheduling
IEQ	CCE (operational)	Ventilation rate and temperature control affect both IEQ compliance and operational energy use	Section 3.2 IEQ; Section 3.3.1 Operational energy and carbon baseline at TalTech
IEQ	CCE (economic evaluation)	IEQ improvements are evaluated together with associated energy, carbon, and cost effects in retrofit assessment	Section 2.3.8 Economic valuation of IEQ improvements; Section 4.2.4 IEQ co-benefits in retrofit economics; Section 4.3.1 Operational carbon footprint patterns
Space efficiency and learning environment	CCE (embodied carbon)	Constructed area and building specifications determine material quantities used for embodied-carbon calculation	Section 2.4.1 Pre-operation carbon footprint within a building's life cycle; Section 3.3.2 Embodied carbon results from QCEPM analysis; Section 4.3.2 Embodied carbon footprint modeling
Transportation	CCE (operational, per-capita)	Transportation emissions and operational carbon indicators use the same population definition and per-capita normalization	Section 2.5.1 PICSOU's transportation indicators; Section 3.4 Transportation; Section 3.3.1 Operational energy and carbon baseline at TalTech
Transportation	Transportation workflow interpretation	Commuting data availability affects workflow choice and reported transportation emissions	Section 2.5.2 Multi-source commuting data acquisition; Section 4.4.1 Inter-workflow comparison; Section 4.4.2 Implications for campus mobility planning and policy

The indicator logic developed in this thesis occupies a methodological intermediate space, as defined in Section 1.6 that sits between general, score-based sustainability assessment tools and institution-specific reporting practices by linking measurable conditions with institution-level sustainability interpretation, and demonstrates that a limited subset of operational indicators captures the main drivers of campus-level sustainability performance.

4.5.2 Overall assessment of the PICSOU framework as a decision tool

This thesis evaluates the PICSOU framework as a decision-support tool by examining whether the indicator structure, calculation logic, and reporting format allow decision-relevant interpretation without aggregation or loss of category-specific information. Evidence from Chapters 2–4 shows that PICSOU supports decision-making by preserving indicator transparency, enabling category-specific interpretation, and allowing results to be examined under different operational and contextual conditions.

Publication 1 defines PICSOU as an indicator-based framework in which each category is evaluated using category-specific indicators derived from measurable operational inputs, without aggregating indicator outputs across categories. This design choice ensures that indicator results remain traceable to their underlying operational variables while avoiding composite scoring that would obscure category-specific behavior. Chapter 2 specifies indicator construction rules, normalization methods, and data requirements for each category.

Chapter 3 demonstrates that the PICSOU indicators can be calculated using empirical data and that the resulting outputs remain interpretable at campus scale. Space-efficiency indicators identify utilization patterns and capacity constraints. IEQ indicators report compliance distributions rather than single-point values. CCE indicators distinguish between operational and embodied carbon components. Transportation indicators report emissions per commuting population under alternative data workflows. These outputs provide category-specific evidence that can be examined independently or in parallel, depending on the decision context.

Chapter 4 shows how these indicators support different types of decisions without requiring methodological modification. Space-efficiency indicators are interpreted in relation to scheduling and allocation decisions. IEQ indicators are interpreted in relation to ventilation control and retrofit prioritization. Operational CCE indicators are interpreted in relation to energy management and per-capita benchmarking. Embodied-carbon indicators are interpreted as a regulatory and planning support tool for new construction and major renovation. Transportation indicators are interpreted in relation to data availability and mobility policy options. In each case, decision-relevant interpretation is derived from the reported indicators themselves rather than from composite scores produced by other scorecard-based sustainability assessment tools.

Taken together, the evidence presented in Chapters 2–4 supports the statement that PICSOU functions as a robust decision-support framework by structuring sustainability assessment around transparent, non-aggregated indicators that remain responsive to shared operational drivers while preserving category-specific interpretation logic.

5 Conclusions

This chapter delivers the conclusive synthesis of the thesis. Reflecting the methodological progression of the research, the chapter is structured to first provide the essential theoretical consolidation for the PICSOU framework developed throughout the appended publications. Sections 5.1 through 5.4 are dedicated to a focused review of the established scholarly literature, standards, and foundational principles pertinent to the key performance indicators within each of the four core categories: space efficiency and learning environment, IEQ, CCE, and transportation. This strategic placement serves a critical function: whereas the introductory chapter established the necessity for a new framework by critiquing existing assessment tools, and the core empirical chapters demonstrated how the PICSOU indicators perform, this concluding synthesis explicitly grounds why the specific indicators were selected and formulated as they were. It connects the empirically derived framework components to the broader academic discourse, thereby justifying their normative basis, operational definitions, and collective coherence. Following this foundational consolidation, Section 5.5 provides direct, evidence-based answers to the overarching research questions. Section 5.6 assesses the achievement of the stated research objectives, Section 5.7 acknowledges the study's limitations, and Section 5.8 proposes actionable directions for future research.

5.1 PICSOU Category 1: space efficiency and learning environment

PICSOU Category 1 links how much space is provided with how well it supports learning, making it central to a climate-neutral yet high quality campus. According to Table 6, this category includes the following KPIs:

- 1.1 Auditoriums and other learning spaces, measured in m^2 per student
- 1.2 Teaching laboratories, measured in m^2 per student
- 1.3 Offices and meeting rooms, measured in m^2 per staff
- 1.4 Total space per person, measured in m^2 per university population (total population = staff + students)

1.5 Self-learning and group-working spaces, measured in number of informal seats over number of formal seats
1.6 Sports facility area per person, measured m^2 per university population (total population = staff + students)
1.7 Ratio of parking space, measured in number of parking spaces per university population (total population = staff + students)

5.1.1 Space efficiency (indicators 1.1-1.4, 1.7)

Efficient provision of teaching, lab and office space reduces construction and operating costs while maintaining functionality. Studies of campus portfolios show that utilization data (frequency and occupancy) directly inform strategic decisions on right sizing education spaces and study places, avoiding unnecessary m^2 while meeting demand [64], [65]. IoT based indicators and occupancy models translate booking and sensor data into percent space utilization and related KPIs, enabling closure or consolidation of under used rooms and associated energy savings [66], [67]. Space utilization studies in higher education further demonstrate that systematic measurement of frequency and occupancy supports both efficiency and future growth planning [64], [68]. Parking space ratios are similarly relevant to space and carbon efficiency, as mobility related floor area and its utilization influence both land take and emissions, and are routinely monitored in campus smart tool portfolios [64].

5.1.2 Learning environment (indicators 1.1-1.4, 1.6)

Provision and configuration of formal and informal learning spaces strongly affect student satisfaction, engagement and performance. Studies of higher education classrooms show that spatial attributes (layout, visibility, furniture, per capita area) and ambient conditions are among the most influential determinants of perceived learning support and satisfaction [69], [70]. Systematic reviews and qualitative studies link indoor conditions and classroom configuration to concentration, emotional state, and short-term academic performance, underscoring that adequate, well designed learning space per user is not a luxury but a precondition for effective teaching and learning [71], [72].

Informal study and group work areas directly support engagement and skills development: studies of student satisfaction highlight class facilities, equipment, and infrastructure as key factors and antecedents of satisfaction [73], [74]. Research on classroom environment shows that physical layout, noise, temperature and lighting significantly shape satisfaction and performance, and motivate IoT enabled “smart classrooms” to tailor conditions to learner needs [75]. Provision of sports facilities per person also relates to wellbeing and engagement through the broader learning environment; campus post occupancy work identifies space efficiency and indoor quality as priority improvement areas in dormitories, libraries and academic buildings, linking them to user satisfaction and functionality [76].

5.1.3 Integration rationale for Category 1

Evidence from occupant centric metrics and campus studies shows that space efficiency and user experience are tightly interdependent. Occupant centric KPIs normalize building performance (e.g., energy per occupant hour) by actual use, making it impossible to optimize resources without simultaneously considering occupancy patterns and user needs [67], [77]. Methodological work on balancing open versus enclosed spaces in university buildings further demonstrates that investment costs, utilization rates, and user satisfaction must be assessed together, and that increasing flexible, multi-purpose open space can yield both economic and experiential benefits [78].

Space utilization analyses that incorporate student perceptions of “crowding” and comfort show that there is an upper bound of utilization beyond which satisfaction declines, implying that efficiency targets must be calibrated to behavioral and psychological responses rather than m^2 alone [79]. Large scale surveys of learning environments similarly indicate that course outcomes are strongly shaped by the quality of the learning environment and student–instructor interactions, beyond formal teaching models [80], [81].

Taken together, this body of work supports treating Space Efficiency & Learning Environment as a single PICSOU category: its KPIs jointly capture (a) how intensively core campus spaces are used per person, and (b) whether the configuration and availability of formal, informal, and recreational spaces enable high quality, engaging, and sustainable learning.

5.2 PICSOU Category 2: IEQ

PICSOU Category 2 focuses on IEQ in typical university space types using a compact set of physical indicators to capture health, comfort and performance relevant conditions on a campus scale. According to Table 6, this category initially includes the following KPIs (based on Publication 1):

- 2.1 Indoor air quality, measured in percentage of spaces meeting category I or category II criteria
- 2.2 General thermal comfort, measured in percentage of spaces meeting category I or category II criteria

Based on cross-climate validation of the IEQ category (Publications 4, 5), the following indicators should also be included:

- CO_2
- $PM_{2.5}$

5.2.1 Thermal comfort (indicator 2.2)

Thermal conditions in educational buildings are repeatedly linked to student health, comfort and academic performance. A large review of 143 field studies concludes that thermal environment is crucial both for wellbeing and energy efficiency in schools and universities, and that inappropriate thermal conditions can compromise learning outcomes [82]. Empirical work shows that exam performance and satisfaction are significantly higher when classroom temperatures fall within a defined comfort band (e.g. 23–26 °C), and that students experiencing discomfort often identify the environment as the main obstacle to performance [83]. Studies comparing different types of university halls also report that only around half of students' votes fall within standard comfort zones, and that feeling cooler is associated with higher perceived productivity, underscoring the need for explicit thermal-comfort KPIs in higher education [84].

5.2.2 Indoor air quality (indicator 2.1), CO_2 and $PM_{2.5}$

Indoor air quality (IAQ), especially CO_2 and particulate matter, is pivotal for health and cognitive functioning in classrooms. A narrative review of IAQ in educational facilities highlights CO_2 as a key parameter influenced by occupancy and ventilation, and PM as strongly affected by building location and activities; both are central to exposure and health risk in schools [85]. IoT-based studies in university buildings use CO_2 sensors as an operational indicator to assess suitable indoor conditions to human activities and to trigger ventilation control so that learning performance is preserved [86].

Empirical work in tropical university classrooms finds that both thermal comfort and CO_2 levels jointly determine overall comfort; short-term comfort ranges (<1095 ppm CO_2; specific temperature and humidity bands) can be identified and used to guide HVAC operation [87]. A systematic review of IEQ and learning in higher education confirms that indoor environmental conditions, particularly IAQ and thermal aspects, can positively contribute to the quality of learning and short-term academic performance [71].

In heritage university classrooms, an integrated IAQ study monitoring temperature, humidity, CO_2 and $PM_{2.5}/PM_{10}$ found that periods of high CO_2 and $PM_{2.5}$ coincided with substantial shares of students reporting headaches, sneezing and fatigue, linking these pollutants to health symptoms and impaired concentration [88]. Global air-quality guidelines also single out $PM_{2.5}$ as a key pollutant requiring strict concentration limits to protect health [89].

Although one controlled-chamber trial with pure CO_2 up to 2100 ppm found no clear harm to adult cognitive performance under fixed ventilation, the authors emphasize that their findings are consistent only for pure CO_2 below 2100 ppm, reinforcing the relevance of monitoring CO_2 in real classrooms where other pollutants co-exist [89].

5.2.3 IEQ compliance

Occupant-based IEQ indicators complement physical measurements by showing how conditions are perceived at population level. Post-occupancy evaluations in university buildings routinely combine monitored thermal and IAQ parameters with satisfaction surveys and often find that temperatures and IAQ are outside recommended ranges while many occupants report being “too cold” or experiencing “stuffy air” and headaches [90]. Comparative studies across campuses quantify satisfaction with IEQ factors such as thermal comfort and indoor air quality and show that differences in IEQ performance between universities can reach around 17%, highlighting the value of standardized satisfaction KPIs for benchmarking [91].

Focused qualitative work in higher-education classrooms demonstrates that poor thermal and indoor air quality conditions affect concentration, emotional state, and decisions about teaching, such as shortening lectures or adding breaks; maintaining acceptable conditions is therefore essential to support learning quality, especially at high occupancy rates [72]. Large multi-building benchmarks also show that overall satisfaction with classrooms depends strongly on IEQ factors such as thermal conditions and indoor air quality, implying that campus-scale satisfaction KPIs are meaningful signals for facility management [92].

5.2.4 Integration rationale for Category 2

Quantitative evidence repeatedly shows that thermal conditions, CO_2, $PM_{2.5}$ and related satisfaction/comfort responses act together to shape health, comfort and learning in educational spaces. Systematic reviews for higher education emphasize that indoor environmental conditions jointly affect attention and test performance, and that thermal comfort and IAQ are the dominant IEQ predictors of academic outcomes [93]. Large thermal-comfort syntheses argue for human-centered, integrated IEQ approaches in educational buildings rather than single-parameter metrics [82].

Within this context, the PICSOU IEQ category combining temperature/humidity, CO_2, $PM_{2.5}$, compliance rates and comfort/satisfaction indicators – matches how the best quantitative studies measure and link IEQ to performance. As an integrated set, these KPIs capture whether campus indoor environments are simultaneously within comfort and air-quality thresholds and perceived as acceptable by occupants, which is exactly the level of diagnostic detail needed for a climate-neutral yet learning-centered campus framework.

5.3 PICSOU Category 3: CCE

PICSOU Category 3 captures how a campus contributes to and mitigates climate change through energy use, low-carbon energy supply and embodied emissions. It focuses on the main levers of reducing a university's GHG emission. Based on Table 6, the following KPIs are included in this category:

3.1 Carbon footprint, measured in tCO_2 per person per annum
3.2 Electricity use, measured in kWh per person per annum
3.3 Heating use, measured in kWh per person per annum
3.4 Primary energy use, measured in kWh per m^2 per annum
3.5 Renewable energy export, measured in kWh per m^2 per annum
3.6 Carbon offset, measured in tCO_2 per person per annum
3.7 Cabon footprint of building materials for new construction and major renovation, measured in $kgCO_2eq$ per m^2

5.3.1 Carbon footprint (indicator 3.1)

Systematic reviews of campus carbon footprints show that HEIs use carbon footprint reports to define mitigation strategies and track progress; electricity, transportation and fuels are the most commonly evaluated sources [94]. A global comparison of 20 universities standardized carbon footprint as t CO_2eq per person and per m^2, finding an order-of-magnitude variation and identifying campuses with <1 t $CO_2eq/(person \cdot a)$ as top performers [95]. Individual case studies likewise report and benchmark emissions per person as a key decision metric [96], [97]. Having $tCO_2/(person \cdot a)$ as a core KPI therefore aligns with emerging practice and enables fair comparison across campuses of different sizes.

5.3.2 Electricity use, heating use and primary energy (indicators 3.2-3.4)

Energy use is the dominant driver of campus GHG emissions. Reviews of university carbon footprint consistently highlight purchased electricity and steam as major contributions (often >40% of emissions) [96]. A systematic carbon footprint review across 49 HEIs found that electric energy consumption was among the three most frequently assessed sources and is central in methodologies established by the International Panel on Climate Change (IPCC) [94].

Energy-benchmarking studies emphasize the need for specific KPIs such as annual energy use intensity ($kWh/m^2 \cdot a$) for meaningful cross-institution comparison and targeted efficiency strategies [98], [99]. Reviews of energy management in universities underline that buildings are major energy consumers and sources of CO_2, and that monitoring and reducing campus energy demand is critical for financial and environmental sustainability [100].

Thus, kWh/(person · a) and primary energy $kWh/m^2 \cdot a$ are indispensable KPIs that connect operational practice with institutional climate targets.

5.3.3 Renewable energy export and carbon offset (indicators 3.5, 3.6)

Surveys of 50 HEIs worldwide show that while many invest in efficiency, only a small portion of energy consumption currently comes from renewables (typically 1–20%), with solar photovoltaic being most common [101]. A state-of-the-art review argues that combining energy efficiency and renewable energy systems is essential to cut energy use, costs and carbon footprints in HEIs and to demonstrate environmental stewardship [99].

Carbon-neutrality case studies show that universities often rely heavily on offsets and unbundled renewable energy certificates, with these instruments representing 77% of reported reductions across 11 U.S. HEIs already claiming neutrality [102]. The authors warn that current neutrality strategies underutilize actual decarbonization (electrification and zero-carbon electricity) and call for clearer accounting of offsets [102].

Including renewable energy export per m^2 and carbon offset per person as KPIs makes these choices transparent: campuses can distinguish between genuine demand-side reductions, on-site renewable generation that displaces grid emissions, and residual emissions managed via offsets.

5.3.4 Embodied carbon of building materials (indicator 3.7)

Operational emissions are not the whole story: campus expansion (new construction) and major renovations embed large amounts of carbon in materials. Life-cycle-based campus carbon footprint studies explicitly include infrastructure construction as a Scope 3 source, recognizing its significant contribution and the need to manage it alongside operational emissions [97].

More broadly, IPCC mitigation pathways emphasize that decarbonizing energy systems and buildings requires attention to both operational energy and material-related emissions over the building life cycle [95]. A KPI in $kgCO_2eq/m^2$

for new construction and major renovation therefore closes a major gap in campus climate accounting, ensuring that expansion strategies are evaluated for their embodied climate impact, not only their energy performance.

5.3.5 Integration rationale for Category 3

Evidence from carbon-footprinting, energy benchmarking and neutrality strategies shows that electricity and primary energy use, low-carbon supply (renewables), offsets and embodied emissions are tightly interlinked in determining a campus carbon footprint. The robust PICSOU framework itself was designed to capture factors having the most prominent impact on buildings' and activities' GHG emissions and to cover more than 80% of Scope 2 and/or Scope 3 footprint with a compact indicator set (Publication 1). Systematic carbon footprint reviews demonstrate that core energy-related sources (electricity, heating, transportation, etc.) dominate HEI emissions and should be prioritized in assessment frameworks [94].

Grouping carbon footprint per person, electricity and primary energy intensity, renewable export, offsets and embodied carbon into one PICSOU category thus mirrors both the scientific understanding of campus GHG drivers and the structure of leading assessment schemes. Together, these KPIs provide a coherent, measurable view of how a university contributes to climate change and how effectively it is transitioning towards genuine climate neutrality.

5.4 PICSOU Category 4: transportation

PICSOU Category 4: Transportation captures how campus-related mobility contributes to, or mitigates, climate impacts. It focuses on commuting and on-campus travel patterns, car dependence, and the shift potential toward low-carbon and active modes, expressed with simple, comparable KPIs across campuses. Based on Table 6, this category consists of the following KPIs:

4.1 Carbon footprint from work trips, business trips, on-campus transportation, measured in tCO_2 per person per annum.

5.4.1 The importance of modal split

Campus studies consistently show that mode choice drives transport emissions and sustainability potential. At the University of Minho, 42% of students drove even though 54% lived within 5 km; modelling indicated that 55% of trips could shift to active modes such as walking or cycling, cutting commuting CO_2 by 8–27% depending on scenario [103]. A Spanish university found that although most commutes were ≤10 km away, car users travelling >6 km generated nearly half of commuting emissions, highlighting modal split and distance as key diagnostic metrics [104].

In a COVID-era case, a shift away from walking, cycling and transit toward cars among those still travelling to campus increased per-trip emissions, and projections showed that if this modal change persisted, the transport carbon footprint would exceed pre-pandemic levels, underscoring the importance of tracking mode shares over time [105].

At city and national scale, modal split is widely used as a proxy indicator for transport sustainability and climate performance; analyses suggest that roughly halving car share with annual reductions of 0.5–1.5 % is needed and feasible, and that modal split remains a robust “fast check” indicator for policy success [106]. Reviews of campus mobility indicators likewise place adequacy of transport modes, public transport, cycling and pedestrian infrastructure, and parking among the 13 key indicators of sustainable mobility for universities [107].

5.4.2 Per-person transport CO_2 and car dependence

Life-cycle and well-to-wheel studies show that commuting dominates transport emissions around campuses and is highly sensitive to mode and occupancy. At the University of León, a detailed LCA of commuting linked modal distribution, distance and travel time to a direct and indirect carbon footprint, revealing substantial mitigation potential through mode shift and improved infrastructure [104].

Outside campuses, high-quality panel and cross-sectional studies quantify how active travel and modal shift reduce CO_2 per person: in seven European cities, each avoided car trip cut daily mobility-related lifecycle emissions by 2.11 kg CO_2, and switching main mode from car to active travel reduced emissions by 9.28 kg CO_2/day [108]. A related analysis found cyclists had 84% lower travel-related lifecycle emissions than non-cyclists and that each additional cycling trip cut emissions by 14%, each avoided car trip by 62% [109].

University-focused work in Pakistan comparing current student travel with a proposed bus system showed that switching private car and motorcycle trips to campus buses could reduce fuel and carbon emissions by 86%, alongside noise and congestion benefits [110]. An Argentinian campus study found that carpooling scenarios could reduce CO_2 by about 26%, again demonstrating the importance of both mode and vehicle occupancy [111].

System-dynamics modelling of Scotland’s passenger transport sector reinforces that modal shift away from cars and toward buses and active modes is one of the most effective interventions for meeting 2030 transport-emission targets, though it must be combined with other measures [112]. Urban analyses using trajectory big data similarly show large carbon-reduction potential when car trips shift to multimodal combinations of active travel and rail [113].

Finally, campus sustainability frameworks consistently include transportation indicators—vehicle numbers, shuttle services, pedestrian and cycling paths, and zero-emission vehicle policies—under their mobility and planning criteria, confirming that such KPIs are now standard in campus sustainability assessment [114], [115].

5.4.3 Integration rationale for Category 4

Empirical campus and urban studies converge on a simple picture: mode share, trip distance, vehicle occupancy and infrastructure jointly determine transport-related CO_2 per person. The PICSOU transportation category groups KPIs exactly along these lines—modal split and active/public transport shares, transport CO_2 per person, and car-related indicators (parking, as measured by KPI 1.7 under Category 1)—providing a compact but powerful lens on campus mobility's climate impact. This integrated set allows universities to diagnose car dependence, quantify emissions, and track the effectiveness of measures that shift trips towards low-carbon and active modes, aligning directly with the best quantitative evidence.

5.5 Answers to the research questions

Section 1.4 of the thesis defines two research questions and three research objectives. This section answers the research questions and accounts for the objectives by referencing how indicator definition, data processing, empirical results, and interpretation are carried out across Chapters 2–4.

5.5.1 Research question 1

What characterizes an effective, practical alternative assessment framework for campus sustainability that does not rely on composite scoring or ranking logic?

This thesis addresses this question by not using composite scoring as the basis for assessment. Instead, it defines a set of category-specific indicators for space efficiency and learning environment, IEQ, CCE, and transportation, and evaluates these indicators separately. Chapter 2 specifies indicator definitions, calculation rules, normalization procedures, and data requirements. Chapter 3 reports indicator results using empirical campus data. Chapter 4 interprets these results at category level without combining indicators into an overall score. The resulting assessment shows how different aspects of campus sustainability change under different operational conditions without relying on composite ranking logic.

5.5.2 Research question 2

What are the functional requirements and demonstrated outcomes of a campus sustainability assessment framework when designed and applied primarily as a decision-support tool for managing core sustainability objectives of campus operation?

This thesis addresses this question by structuring the assessment around indicators that are directly linked to measurable operational variables. Chapter 2 defines indicators using data sources that are available within campus operations. Chapter 3 quantifies indicator outcomes using monitored, metered, or documented data. Chapter 4 links indicator results to specific decision contexts, including space allocation and scheduling, ventilation and retrofit prioritization, operational and embodied carbon interpretation, and commuting data selection. The assessment therefore supports decisions by showing how changes in operational conditions affect indicator outcomes, rather than by assigning symbolic ratings.

Therefore, in response to RQ2, this thesis demonstrates that an assessment framework like PICSOU can and should function as a practical operational tool. Its results are primarily relevant to campus operations managers, sustainability officers, and planning committees. They should use indicators to diagnose specific operational performance gaps (e.g., in space utilization, IEQ, or commuting emissions), benchmark performance against climate neutrality goals, and inform targeted infrastructure investments and policy changes, thereby directing measurable improvements across university campuses.

5.6 Achieved research objectives

The three objectives stated in Section 1.4 are addressed as follows.

5.6.1 Research objective 1

To identify a practical approach for assessing campus sustainability using indicators that reflect measurable operational performance and limit dependence on incompletely verifiable inputs.

This objective is met by defining indicators that are calculated from timetable data, occupancy information, monitored IEQ data, metered energy use, material quantities, and commuting datasets. Chapter 2 specifies how each indicator is calculated and what data is required. Chapters 3 and 4 apply these indicators using empirical datasets without introducing proxy scores or subjective weighting.

5.6.2 Research objective 2

To analyze the trade-offs associated with different assessment methods and determine how these trade-offs affect the accuracy and usefulness of assessment outcomes.

This objective is met by applying alternative assessment workflows within the same indicator category. In the transportation category, Chapter 3 applies both survey-based and ICT-based commuting workflows using the same population definition. Chapter 4 compares the resulting outputs and discusses how data availability and methodological choice affect reported emissions without changing indicator definitions.

5.6.3 Research objective 3

To develop evidence-supported recommendations for improving campus sustainability assessment practices, with emphasis on indicator relevance, data requirements, and applicability across institutions.

This objective is met by interpreting indicator results in relation to specific application contexts in Chapter 4, including space management, IEQ benchmarking, energy and carbon management, embodied-carbon regulation, and campus mobility planning. Section 4.5 consolidates these interpretations by identifying shared operational drivers across categories while maintaining separate indicator outputs.

5.7 Limitations of the study

5.7.1 Scope, design, and narrative

This thesis is subject to limitations that arise from data availability, sample size, methodological scope, and framework design choices reflected across the appended publications. These limitations define the conditions under which the results presented in Chapters 2–4 should be interpreted.

First, several indicators rely on datasets collected for operational or administrative purposes rather than for sustainability assessment. Space-efficiency indicators are derived from timetable and booking records that describe scheduled use rather than continuous real-time occupancy. Although occupancy detection methods are applied for IEQ assessment, comparable occupancy resolution is not available for all indicator categories. As a result, some indicators represent planned or aggregated conditions rather than instantaneous operational states.

Second, the spatial and temporal coverage of empirical datasets differs across categories. IEQ indicators are calculated from monitored data collected in selected rooms rather than across the full campus building stock. Transportation indicators are calculated for a defined population. Operational energy and carbon indicators are derived from metered data aggregated at building or campus scale. These differences limit direct spatial and temporal alignment between categories and restrict the level of disaggregation that can be applied consistently across all indicators.

Third, the IEQ assessment is constrained by limited sample size. As discussed in Publication 5, IEQ indicators are calculated from measurements collected in a restricted number of rooms rather than from statistically representative samples of the entire campus building stock. The monitored rooms are selected based on data availability and access constraints. The reported IEQ distributions and cross-campus comparisons therefore describe observed conditions in the monitored spaces rather than population-level IEQ performance across the campus.

Fourth, the transportation assessment is subject to methodological and data-related constraints identified in Publication 2. Survey-based (conventional) commuting carbon footprint auditing workflow depends on self-reported travel behavior and generalized assumptions regarding travel distance and time. ICT-based (novel) commuting carbon footprint auditing workflow relies on sampled and filtered mobility data produced using proprietary algorithms, with limited transparency regarding data processing. Differences between alternative commuting workflows reflect differences in underlying assumptions, data resolution, and filtering procedures rather than measurement error alone. Transportation indicators therefore remain sensitive to population definition, temporal scope, and data availability.

Fifth, the study does not apply causal inference methods to quantify causal relationships between indicators. Although Section 4.5.1 shows that multiple indicator categories respond to shared operational drivers, the thesis does not estimate causal magnitudes or directionality. The analysis is limited to identifying alignment and co-occurrence of indicator responses under observed operational conditions.

Finally, the embodied-carbon assessment is constrained by the scope of the QCEPM model discussed in Publication 3. The embodied-carbon indicator addresses new construction and major renovation using building material quantities and emission factors but does not include minor refurbishment activities or detailed supply-chain differentiation. In addition, the embodied-carbon case study is conducted on a building stock that differs from the campuses used for operational indicator analysis. These limits direct numerical comparison between operational and embodied carbon results within a single physical system.

Together, these limitations define the analytical boundary of the study and clarify how the results of the PICSOU framework should be interpreted when applied to campus sustainability assessment.

5.7.2 Assessment paradigm

5.7.2.1 Focus on measurable performance

A key conceptual limitation of this research is its necessary narrowing of the "sustainability" concept to aspects that are quantifiable and directly tied to campus operations. The thesis prioritizes the development of a robust diagnostic tool, which requires focusing on variables like energy, carbon, space use, and transportation—domains where performance can be empirically measured and verified. This operational focus, while critical for creating a practical decision-support framework, means that broader, equally important dimensions of sustainability such as social equity, education for sustainable development, community engagement, and the university's role as a societal actor are not encompassed within the assessment boundary. The study therefore contributes to a specific, infrastructure-led narrative of campus sustainability. It is acknowledged that this framing, while effective for its stated purpose, does not represent a holistic view and may inadvertently marginalize non-quantifiable sustainability outcomes that are central to the university's mission.

5.7.2.2 Design logic of a minimum KPI set

The PICSOU framework is built on the principle of a "minimum set of KPIs" to ensure practicality and cross-campus applicability. A significant limitation lies in the inherent trade-offs of this design choice. Selecting a minimal set of indicators based on resource flows and building performance necessarily simplifies the complex reality of a campus as a social-ecological system. This simplification carries the risk of omitting context-specific drivers, indirect effects, and long-term systemic interactions that are crucial for a complete understanding of sustainability performance. The framework's strength as a universal diagnostic tool is thus counterbalanced by its potential reductionism. It provides a clear, comparable snapshot of core operational performance but may not capture emerging issues, behavioral aspects, or unique local priorities that fall outside its predefined categories. The justification for this minimal set is therefore not just about practicality but also an acknowledgment of a deliberate, and limiting, boundary drawn around what is being measured.

5.7.2.3 Schematic use of the SDGs

The thesis uses the SDGs as a high-level referential framework to situate the research, as illustrated in Figure 12. A major limitation is the schematic nature of this linkage. The connection between the PICSOU categories and specific SDGs is indicative, showing areas of potential contribution, but it is not the result of a rigorous, bottom-up mapping of the research metrics onto official SDG targets and indicators. Consequently, the figure should be interpreted as a communication of scope and intent rather than as evidence of direct, measured impact on the SDGs. This highlights a common challenge in sustainability science: translating grand global goals into specific, accountable local metrics. The study demonstrates how operational campus data can address themes related to the SDGs, but it does not establish a formal, traceable reporting line to them, which is a limitation in terms of integrating the findings into broader SDG monitoring and reporting frameworks.

5.7.2.4 Structure-limited synthesis

The organization of the Discussion chapter (Chapter 4) is shaped by the source publications, leading to a structure that analyses each sustainability category (space, IEQ, CCE, transportation) in sequence. A clear limitation of this approach is that it prioritizes a deep, category-specific validation of results over a continuous, thesis-level synthesis aimed directly at the overarching research objectives. While this ensures each PICSOU category is thoroughly examined, the integrated discussion of cross-category interactions, trade-offs, and the collective contribution of the findings to the PICSOU framework as a whole becomes more episodic, featured primarily in Section 4.5. The highest-order synthesis, which reframes the collective evidence to answer the core research questions and assess the framework's overall value, is therefore accomplished in the concluding Chapter 5. This structural delineation between domain-specific discussion and final synthesis is a narrative choice that, while logical, means the critical, integrative reasoning that defines the thesis's main argument is consolidated at the end rather than being the driving force throughout the discussion narrative.

5.8 Directions for future research

5.8.1 Empirical and methodological advancement

Future research directions follow directly from the methodological scope, data constraints, and framework design choices identified in Chapters 2–4 and summarized in Section 5.5.1. These directions indicate where additional evidence or methodological refinement would extend the applicability of the PICSOU framework without altering its indicator structure.

First, future work should expand the spatial and temporal coverage of empirical datasets used for indicator calculation. In particular, IEQ assessment would benefit from monitoring campaigns that include a larger number of rooms, additional space types, and longer observation periods. Extending the monitored sample would allow assessment of whether the IEQ distributions observed in Publication 5 remain stable across a broader range of campus spaces and seasons, and would reduce uncertainty associated with limited sample size.

Second, future research should examine methods for improving temporal alignment across indicator categories. Chapters 2 and 3 apply indicators using datasets collected over different time periods and at different temporal resolutions. Coordinated data collection strategies, in which space-use data, IEQ monitoring, energy metering, and commuting data are collected over overlapping periods, would allow closer examination of how indicator responses align under the same operational conditions. Such work would strengthen cross-category interpretation without requiring indicator aggregation.

Third, further development of occupancy measurement methods would improve indicator accuracy across multiple categories. While occupancy detection is applied explicitly in IEQ assessment, comparable occupancy resolution is not available for space-efficiency, energy, or transportation indicators. Future studies could evaluate the impact of higher-resolution occupancy data on space-efficiency indicators, per-capita normalization of energy indicators, and interpretation of transportation emissions.

Fourth, future research should extend the embodied-carbon assessment to additional construction scopes and building types. Publication 3 focuses on new construction and major renovation using the QCEPM model. Extending this analysis to include minor refurbishment activities, alternative structural systems, or different regulatory contexts would improve the applicability of the embodied-carbon indicator under the CCE category. Applying embodied-carbon assessment to campus-specific building stocks would also support closer numerical comparison with operational carbon indicators.

Fifth, additional research should examine transportation indicators under expanded data conditions. Publication 2 applies parallel survey-based (conventional) and ICT-based (novel) commuting carbon footprint auditing workflows for a defined population and observation period. Future studies could evaluate the stability of transportation indicators across different academic calendar phases, longer observation periods, or alternative population definitions. This would clarify how sensitive reported transportation emissions are to temporal scope and data source selection.

Finally, future work could examine formal methods for analyzing relationships among indicators without introducing composite scoring. Section 4.5.1 identifies shared operational drivers across categories, but the thesis does not apply causal inference or system-level modelling. Future research could test analytical methods that quantify relationships among indicators while preserving separate indicator outputs, consistent with the non-aggregated framework logic defined in Publication 1.

Together, these directions indicate that future research can extend the empirical basis and analytical resolution of the PICSOU framework while maintaining its core design principles: transparent definition of limited number of core indicators, non-aggregated reporting, and applicability across institutional and climatic contexts.

5.8.2 Paradigmatic and transformative agendas

The development and validation of the PICSOU framework, as presented in this thesis, does not represent a closed endpoint but rather establishes a foundation for a progressive and critical research agenda. The framework's deliberate focus on operational, measurable performance—while its core strength—also explicitly delineates the boundaries of its current application. The future research directions outlined below are conceived as structured pathways to interrogate, expand, and transcend these boundaries. They are organized not as a simple list of technical extensions, but as a coherent, multi-layered program addressing methodological refinement, conceptual integration, contextual expansion, and the translation of evidence into practice and policy. This agenda directly responds to the identified limitations of the study and aims to propel the field of campus sustainability assessment towards greater rigor, relevance, and transformative potential.

1. **Advancing the research paradigm: from validation to critical reflection**

Future work must evolve from merely applying the PICSOU framework to critically examining the assessment paradigm it represents. This involves:

- Paradigm interrogation: Conducting comparative studies that explicitly contrast the diagnostic, operational logic of PICSOU with the symbolic, composite-score logic of prevailing ranking systems (e.g., UI GreenMetric, STARS). Research should investigate not only the outcomes but the epistemological and practical consequences of each approach: How do they shape institutional priorities, allocate resources, and construct the very meaning of "sustainability" within a university?
- Epistemic critiques: Engaging with philosophy of science and science and technology studies to critically analyze the reductionist choices inherent in any indicator-based framework. Future research could explore: What socio-technical arrangements and sustainability imaginaries are reinforced or marginalized by a focus on energy, carbon, and IEQ? How can frameworks be designed to be more reflexive about their own normative assumptions and political effects?

2. **Methodological evolution: deepening robustness and expanding scope**

The methodological core of the PICSOU framework requires continuous testing, refinement, and innovation to enhance its scientific robustness and practical utility.

- Indicator development and calibration: A priority is the large-scale, cross-contextual validation of the proposed indicators, particularly the diagnostic parameters for IEQ (e.g., λ_{season}, I/O ratio) and the QCEPM. This requires expanding case studies to diverse climatic zones (tropical, arid, polar) and institutional types (non-residential, distributed campuses) to derive context-sensitive benchmarks and uncertainty ranges. Furthermore, research should explore the integration of emerging, high-resolution data sources, such as IoT sensor networks and digital twins, to move from periodic assessment to continuous, predictive performance monitoring.
- Integration with established tools: The practicality of the framework hinges on its interoperability. Future research should develop and test formalized methodologies for integrating PICSOU indicators with established planning and management tools, such as Building Information Modelling (BIM) for new construction, Geographic Information Systems (GIS) for spatial and mobility planning, and campus-level LCA to evaluate the long-term trade-offs between operational improvements and embodied impacts of campus development.
- Longitudinal and causal analysis: Moving beyond cross-sectional case studies, a crucial direction is the design of longitudinal research programs. Tracking the same set of PICSOU indicators over multiple years, especially before and after major interventions like deep retrofits or mobility policy changes—would allow for robust analysis of trends, causal relationships, and the long-term effectiveness of sustainability measures, thereby addressing a key gap in current evidence-based campus management.

3. **Contextual and geographical expansion: testing universality and equity**

The "universal" claim of the framework demands rigorous testing against the vast heterogeneity of global higher education.

- Focus on the Global South and underrepresented contexts: A significant research imperative is to actively apply and adapt the PICSOU framework in universities across the Global South, in regions with constrained resources, unreliable energy grids, or different pedagogical traditions. This research must confront questions of data scarcity, cost, and cultural relevance, potentially leading to simplified "core" indicator sets or alternative proxy measures, thereby ensuring the framework's utility is not limited to well-resourced, data-rich institutions in the Global North.
- Equity and justice dimensions: The current framework focuses on environmental performance. Future research must develop robust, quantitative methodologies to link these operational metrics to dimensions of social and spatial equity on campus. This could involve, for example, analyzing disparities in IEQ or space efficiency across different buildings or

user groups (e.g., staff vs. students, different faculties), or evaluating how transportation infrastructure and policies affect accessibility for diverse socioeconomic groups.

4. **From measurement to transformation: bridging analysis, policy, and governance**

The ultimate test of any assessment framework is its ability to inform and improve decision-making. Future research must bridge the gap between measurement and action.

- Organizational and policy analysis: Scholarly attention should shift towards the "demand side" of assessment tools. This involves interdisciplinary research combining management studies, political science, and organizational sociology to understand: What are the institutional drivers, barriers, and pathways for adopting operationally focused frameworks like PICSOU? How can sustainability data be effectively communicated to and utilized by different stakeholder groups (facility managers, financial officers, university leadership)?
- Fostering learning communities and benchmarking: Research can explore the design and impact of novel governance mechanisms, such as sector-wide "benchmarking clubs" or data consortia where universities confidentially share PICSOU indicator data. Studying such collaborations can yield insights into effective peer-learning models, the development of sectoral performance baselines, and the role of transparency in accelerating collective progress towards climate neutrality.

5. **Engaging with grand challenges: the university in the Anthropocene**

Finally, the PICSOU framework provides a lens through which to examine the university's broader role in societal transitions. Future research can position campus operational performance within larger discussions on:

- SDG reporting and impact: Developing rigorous, traceable methodologies to connect specific PICSOU indicator outcomes (e.g., reduced carbon footprint per person, improved IEQ compliance) to contributions towards specific Sustainable Development Goal (SDG) targets, moving beyond schematic linkages to demonstrate measurable, accountable impact.
- Living labs and societal learning: Conceptualizing the instrumented, assessed campus as a "living lab." Research can investigate how real-time performance data and assessment outcomes can be integrated into curricula, citizen science projects, and public engagement, thereby transforming the campus from a passive object of measurement into an active site for co-learning and demonstration about sustainable living in the Anthropocene.

This multi-faceted research agenda acknowledges that advancing campus sustainability is as much a conceptual, social, and institutional challenge as it is a technical one. By pursuing these directions, future work can build upon the PICSOU foundation to develop not only genuinely robust assessment tools, but also a richer, more critical, and more impactful practice of sustainability in higher education.

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Performance based core sustainability metrics for university campuses developing towards climate neutrality: A robust PICSOU framework

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ABSTRACT

Despite the global interest, the sustainable development of universities remains commonly unmonitored as existing tools are either overly complicated or less specific for university campuses. Evaluation of existing tools motivated this study to focus on measuring sustainability performance of university campuses. By concentrating on factors having the most prominent impact on buildings' and activities' greenhouse gas (GHG) emissions and social performance, PICSOU (Performance Indicators for Core Sustainability Objectives of Universities), a six-category framework with about 20 key performance indicators (KPIs) was identified to monitor more than 80% of Scope 2 or/and Scope 3 carbon footprint of a university campus and enables relatively easy cost-benefit analysis of potential improvements. Proposed categories and KPIs are general, but the improvement measures can always have a local origin. To test the framework, a case study was conducted and findings include discovery of lowutilization spaces, potential parking footprint reduction, co-benefits exceeding energy savings in renovation and an annual carbon footprint of 1.3 tCO2eq per university population. This study showcases the latest endeavor in identifying a simple and robust framework containing universally measurable indicators that are easily compatible with different campuses and can enable the timely and accurate measuring of university campus sustainability

1. Introduction

1.1. A university campus' role in sustainable development

It is safe to presume that the consequences and costs of climate change on our world will define the 21st century (Koubi, 2019), especially given the latest unsettling geopolitical predicaments amidst an ongoing global pandemic, one imposing great setback on many already belated and under-implemented climate change mitigation agendas. The key to altering climate change is to reach net zero carbon emissions, and the building sector has long been a major area of focus for achieving such goal, thanks to its 40% share of total energy use and GHG emissions (Pérez-Lombard et al., 2008) resulting from electricity and heat production by fossil fuel, as we spend on average 90% of our time indoors (Klepeis et al., 2001). With their diverse function and scale, universities can be considered small communities, providing relatively easy access to data at both the stand-alone buildings' level and the community level, contributing to global sustainability through their education, research and the operation of their own estate (Gu et al., 2019). For such reason, there has been a global trend to develop assessment tool for university campus sustainability based on a principle known as the 3Ps (three pinciples: social, environmental, social, and economic), which reflects that responsible development requires taking into consideration the natural, human, and economic capital (Elkington & Berkovics, 1997) (Kajikawa, 2008) (Schoolman et al., 2012) while fulfilling the objectives set forward by the UN's 17 Sustainable Development Goals (SDGs). 1.2 Problems with existing assessment tools for university campus sustainability

1.2.1. Green building standards

Sustainable buildings have been widely acknowledged as an integral part of the solution to the environmental challenges; such topic has also become the impetus behind the development and application of scientific tools for the sustainable design, construction and operation of buildings. Among them, popular rating systems such as BREEAM (Building Research Establishment Environmental Assessment Method) and LEED (Leadership in Energy and Environmental Design) are appropriate examples of comprehensive technical standards for energy

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efficient and environmentally friendly buildings known as the green buildings. However, there is a dearth of information and insight on the relationship between the assessment criteria of green building rating systems and the UN SDGs (Alawneh et al., 2019) and a green building does not always use less energy (Newsham et al., 2009) (Scofield, 2009), a previous study on a major university campus in the US suggested no clear trends in energy savings of LEED-certified buildings was observed either at individual building or portfolio level (Agdas et al., 2015). While the argument on the suitability of using green building standards interchangeably as the measuring tool for university campus mostly focuses on the technical aspect, we found the statistics of university projects certified under BREEAM and LEED more objective and forthright indicative.

1.2.1.1. BREEAM. Developed by BRE (the Building Research Establishment) in 1990, BREEAM is the first green building rating system in the world, and continues to be one of the world's most influential green building rating systems with more than 2.3 million registered buildings in 93 countries (BREEAM, 2022). Using third-party-certified standards, BREEAM can assess any type of building based on 10 credit categories each having certain number of points based on the category's importance: energy, management, health and wellbeing, transport, water consumption and efficiency, materials, waste, pollution, land use and ecology, innovation. Based on the percentage of final score over total score, a BREEAM project can receive different certification level raging from the lowest "Pass" (>=30%) to middle levels like "Good" (>=45%), "Very Good" (>=55%), "Excellent" (>=70%), to the highest "Outstanding" (>=85%). To observe the most representative BREEAM-certified university buildings, we applied series of filters to BRE's project database and came up with the following observation:

To exclude obsolete projects, the superset consists of only 29,579 projects certified using BREEAM's 2008 schemes and onwards (as of September 2022), of which, 3006 falls under the project type of "Education". Considering "energy" and "health and wellbeing" are the two BREEAM credit categories with the highest points and account for more than 35% of total scores, it is impossible for projects receiving "Excellent" or "Outstanding" level certification to score poorly under these two categories, which also contribute directly to a building's carbon footprint (it is only possible to observe a project's total percentage of score without a categorical break-down). After applying the certification level filter, we were left with 967 projects. To decide which of these projects are university projects, we manually screened each project based on project scheme (for projects located in the UK certified using the BREEAM UK standards) or project description (for international projects using the BREEAM International standards or country-specific standards in countries where a national scheme operator is available), and ended up with 267 projects. These projects are considered good examples of sustainable university campus building, but they tend to over concentrate in the UK with only a dozen more projects found in other European countries, covering a limited fraction in the total climate classifications (see Fig. 1).

To conclude the above observation, though globally recognized as a comprehensive rating system with rigorous score criteria, when BREEAM is used to certify university buildings, apart from the dominant number of successful cases in the UK, the sample size outside the UK is still rather small and inexhaustive of climate classifications, an evident indicator for insufficient universality.

1.2.1.2. LEED. Inspired by, and based on BREEAM, LEED is known as the world's most widely used rating system for green buildings (U.S. Green Building Council, 2022) with more than 900 million m^2 of certified area in over 190 countries/regions, it is a third-party-verification green building rating system developed and managed by USGBC, (the U.S. Green Building Council) whose rating scheme covers all building types, including new construction, existing buildings, homes and communities. LEED has 9 areas of focus, including location and transportation, sustainable sites, water efficiency, energy and atmosphere, material and resources, indoor environmental quality, innovation, regional priority, and integrative process. Based on the total performance score from these 9 areas, a building can receive one of the four certification levels including certified, silver, gold, and platinum. Despite its evident popularity and rapid market growth, the use of LEED in assessing university campus sustainability has not been on par. We applied series of screening filters in USGBC's project directory and came up with the following observation:

Of all 173,189 registered LEED projects (as of September 2022), 139,794 projects' information is non-confidential and can be publicly accessed, of which, only 2800 are projects matching the LEED project

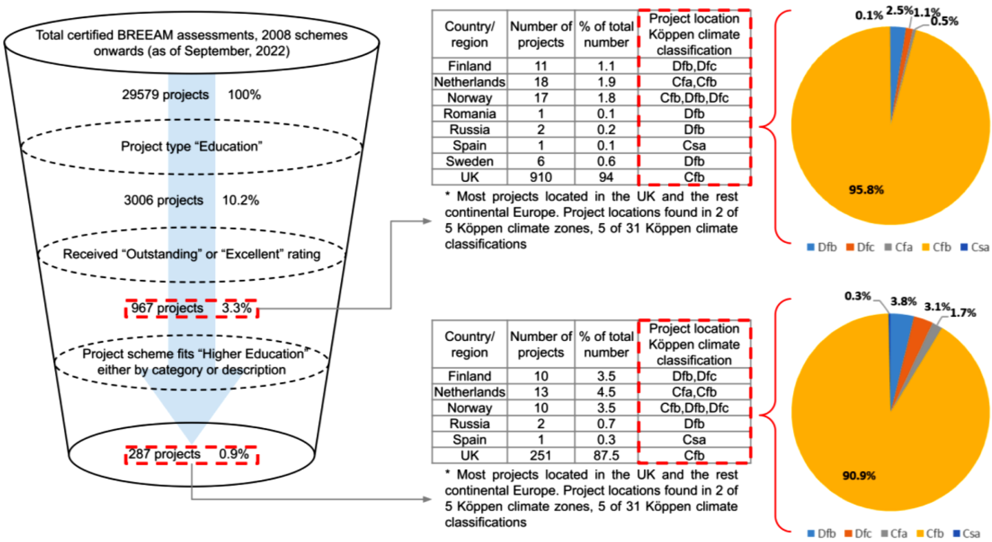


Fig. 1. Screening of BREEAM projects and analysis of key projects' distribution of locations and Köppen climate classifications.

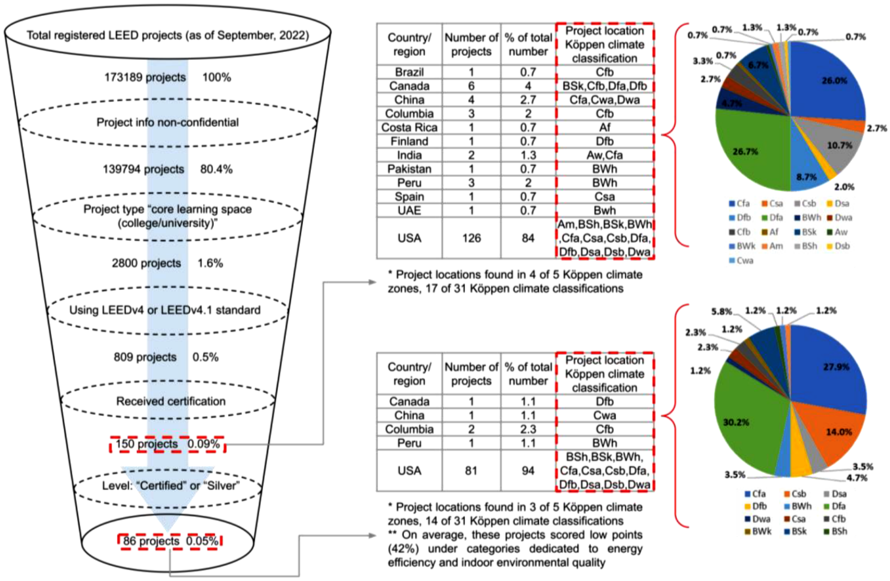


Fig. 2. Screening of LEED projects and analysis of key projects' distribution of locations and Köppen climate classifications.

type of "core learning space: college/university". Since LEED has been continuously updating its reference guide to keep up with the latest technical requirement, LEEDv4 and LEEDv4.1 are the latest version while all preceding versions have phased out by the end of 2016. Of all 2800 LEED projects under the "college/university" project type, only 809 projects from 29 countries/regions registered between 2009 and 2022 are evaluated using the latest version of LEEDv4 or LEEDv4.1, of which, 390 projects have failed to receive certification within their project's two-year validity of registration, only 150 have been successfully certified. Of the 150 certified projects, more than half (86) received the lower-tier certification of "Certified" or "Silver", of which, as many as 81 are located in the US (see Fig. 2). Among these 86 projects, their average total score from both the Energy and Atmosphere (EA) category and the Indoor Environmental Quality (EQ) category is 21 points - around 42% of the total available points from these two categories (49 or 55 points depending on the rating system). We also noticed several extreme cases, in which, a project with very low score from the EA and EQ categories (7 points in total) received "Certified" level certification; a few projects with "Certified" level certification have higher total points from EA and EQ than many of their "Silver" level certified counterparts, yet because they did not score as many points from other categories, they received overall lower scores and thus lower certification level, and are considered less "green" in the real estate market.

Based on the above observation, we were able to conclude that LEED's latest standards have become less popular among university campuses both in terms of total registered projects and total certified projects. The certified university projects, which are otherwise looked up as good examples of sustainable university campus building, tend to over concentrate in the US with the majority achieving only the lowest certification requirements, whose points mainly come from categories not directly (if at all) contributing to carbon footprint reduction, which can be very misleading in reflecting a building's actual level of sustainability. This further jeopardizes LEED's universality and compatibility with university campuses located in different climate zones.

1.2.2. Sustainable campus rating systems

Over the past 20 years, university rankings, allowing to classify and compare the energy and environmental performance of university buildings and campus, have become more and more widespread and their diffusion is still increasing by means of referred established models (Marrone et al., 2018) with typical examples like the Nixon's Campus Sustainability Assessment Review Project in 2002 (Nixon, 2002), which includes reporting and questionnaires limited to the internal recognition of impact on environmental and self-assessment by an individual campus, and therefore could not be used to make the comparison among different universities (Shuqin et al., 2019). Some other indices evaluation systems, such as the Campus Sustainability Selected Indicators Snapshot and Guide by Shriberg mainly focus on the operational eco-efficiency, and give a quick overview of campus operations and environmental influences (Shriberg, 2002). GREENSHIP contains 6 categories: appropriate site development, energy efficiency and conservation, water conservation, material resources and cycle, indoor health and comfort, and building environment management (Lauder et al., Dec. 01, 2015). The USAT (Unit-Based Sustainability Assessment Tool) (Togo & Lotz-Sisitka, 2009) and the AUA (Alternative University Appraisal) project consider issues in environmental and economic aspects (Abdul Razak et al., 2013). Some systems attempt to cover all important issues of sustainable development (SD), including energy, water, food, land, transportation, built environment, community, research, education, outreach, and decision-making (U.S. Green Building Council, 2019). the Sustainability, Training, Assessment and Rating System (STARS) is a transparent self-reporting framework open for all higher education institutions to evaluate their performances of SD in different fields of operation, education, research and outreach (Shuqin et al., 2019).

1.2.2.1. UI GreenMetric World University Rankings. To promote sustainable development, it will be necessary to establish a carbon emissions accounting system applicable to university campuses and to formulate a reasonable carbon emissions reduction target (Li et al., 2022). One of the latest universal tools developed for crediting universities' efforts in reducing their carbon footprint is the UI GreenMetric World University Rankings system, a 6-criteria evaluation tool with 39 indicators. Launched in 2010, it is now the world's most recognized stand-alone sustainability ranking for universities with over 900 participating institutions from 80 countries (UI GreenMetric, 2022). We studied UI GreenMetric's questionnaire for reporting university sustainable features and came up with the following observation:

1 Several crucial indicators such as total ground floor area, total university budget and annual per person carbon footprint do not require provision of evidence, which potentially affects the authenticity of the submitted data.
2 The questionnaire partly refers to existing systems such as LEED and STAR (this system itself refers frequently to LEED).
3 Depending on the focus of each year's ranking, indicators are undergoing constant update and amendment, lacking consistency in criteria composition.
4 Carbon footprint calculation considers only electricity use and transportation, but not heating, this does not reflect reality and greatly affects the accuracy of submitted data.
5 Each of the 6 evaluation categories has fixed percentage of weight, this one-size-fits-all configuration is very unlikely to adapt well to different local contexts.

1.3. Research concept of this study

Through the above observation on the most recognized green building rating systems and university sustainability ranking tool, we concluded that all these tools' suitability for assessing university campus sustainability is limited by their universality and objectivity. From this conclusion arise also critical questions:

1 Is certification/ranking the best way to assess/showcase a campus' level of sustainability?
2 Should a certificate/ranking serve as a feel-good badge or a guideline for further improvement?

Inspired by these questions, we sought to identify, in this study, a simple and robust framework that focuses only on measuring core performance instead of achieving high scorecard performance. Unlike nowadays' immensity of complex tools, the framework aspires to contain only a minimum number of KPIs. The objectives of this study include:

1 To identify a practical framework with KPIs for continuous measurement and improvement of university campus sustainability
2 To devise cost-benefit analysis within the applicable university sustainability categories of the identified framework
3 To provide evidence-based suggestion for action plan on sustainable university campus developing towards climate neutrality

Through this study, categories and KPIs developed were expected to facilitate senior management personnel of universities to focus on essential sustainability improvement areas instead of minor issues with minimum or negligible impact.

2. Materials and methods

2.1. Cost-benefit analysis

The different pillars of the 3Ps and their associated SDGs are not always in harmony, but rather, constantly at odds with each other. Achieving the optimal trade-off among different SDGs is the ultimate justification of this study, and calls for cost-benefit analysis, without which, the study will fall short in its impartiality. Studies using the cost-benefit analysis considering energy costs and carbon emission offsets have indicated a substantially larger productivity benefit than its incremental energy cost with negligible effect over the cost for carbon offset (McArthur, Feb., 2020). To perform the cost-benefit analysis in the simplest fashion, we utilized the following equations:

$$Simple\ Payback\ Time = \frac{Incremental\ Cost}{Incremental\ Benefit} \tag{1}$$

Where *Incremental Cost* and *Incremental Benefit* was calculated using Eq. (2) and Eq. (3) respectively:

$$Incremental\ Cost = Unit\ Area\ Renovation\ Cost * Building\ Area \tag{2}$$

$$Incremental\ Benefit = Total\ Monetized\ Productivity\ Increase + Total\ Monetized\ Energy\ Saving \tag{3}$$

For Eq. (3), *Total Monetized Productivity Increase* was calculated using Eq. (4):

$$Total\ Monetized\ Productivity\ Increase = Employee\ Compensation * Building\ Area * Average\ Occupant\ Density * Productivity\ Increase \tag{4}$$

Fig. 3. Aerial image of TalTech's Mustamäe campus, compass rose placed at the same geographic location as shown in Fig. 4 but facing opposite direction to provide perception of campus layout from different angles.

For Eq. (4), *Productivity Increase* was calculated using the sum from Eq. (13) in Section 3.1.2.4 of this paper. *Total Monetized Energy Saving* was calculated using Eq. (5):

$$Total\ Monetized\ Energy\ Saving\ = Building\ Area^{*}\sum_i e_i{}^{*}P_i \tag{5}$$

In which, e_i is the unit area saving from different types of energy use, typically include electricity and heating (depending on the source, it can be either district heating or natural gas), P_i is the respective unit energy price.

In addition to energy saving and productivity increase, monetized unit area carbon reduction is also a good metric and an integral part of the benefit of renovation, which was measured in terms of marginal abatement cost (*MAC)*, the quotient of net present value (*NPV)* divided by *Unit Area Carbon Reduction*:

$$MAC = \frac{NPV}{Unit\ Area\ Carbon\ Reduction} \tag{6}$$

Where:

$$NPV = -B + a^{*}\frac{1-[1+(i_a-i_e)]^{-n}}{i_a-i_e} \tag{7}$$

In which, B is same as *Unit Area Renovation Cost* in Eq. (2), a is the monetized unit area annual energy saving, also known as net cash flow, calculated using current energy price, i_a is annual interest rate (set at 4%). i_e is the default annual energy price escalation (set at 2%), n is the number of payback years (set at 20).

And:

$$Unit\ Area\ Carbon\ Reduction = \sum_i E_i{}^{*}f_i \tag{8}$$

In which, E_i is the annual energy saving from specific type of energy use within a unit area, f_i is its respective emission factor. Considering the emission factor for both heating and electricity will decrease over time, unit area's carbon reduction throughout the payback period from heating and electricity was calculated by applying different emission factor for different timespan within the payback period. While Eq. (1) and Eq. (6) were used for calculating renovation payback time and carbon reduction cost, it is evident that the same calculation may be applied to any other action having an investment cost, monetized benefits and carbon impacts, related for instance to transportation, waste or space efficiency improvement measures.

2.2. Campus buildings

All data for the case study in this paper were collected from buildings on the Mustamäe campus (see Fig. 3) of Tallinn University of Technology (TalTech).

Established in 1918, TalTech is the only university of technology in Estonia providing higher education at all levels in engineering and technology, information technology, economics, science, and maritime. Mustamäe is TalTech's main campus and home to 9691 students and 985 academic staff, it is the only campus-type university in the Baltic countries and one of the most compact university campuses in Europe. The Mustamäe campus consits of 19 university buildings (excluding buildings belonging to the Tehnopol Science and Business Park which shares part of the campus site), 1 track field, 7 dormitories and 1 hostel. To have a more realistic overview of campus energy use, we looked into data over a 3-year period (2017 – 2019) prior to the outbreak of the COVID-19 (COronaVIrus Disease 2019) pandemic (during which, the university instigated home office to comply with social distancing regulations and resulted in a rather low occupancy, which might not

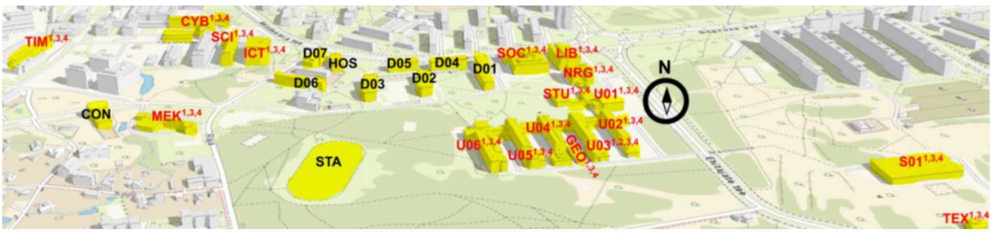


Fig. 4. Map of TalTech's Mustamäe campus, compass rose placed at the same location as shown in Fig. 3 but facing opposite direction to provide perception of campus layout from different angles.

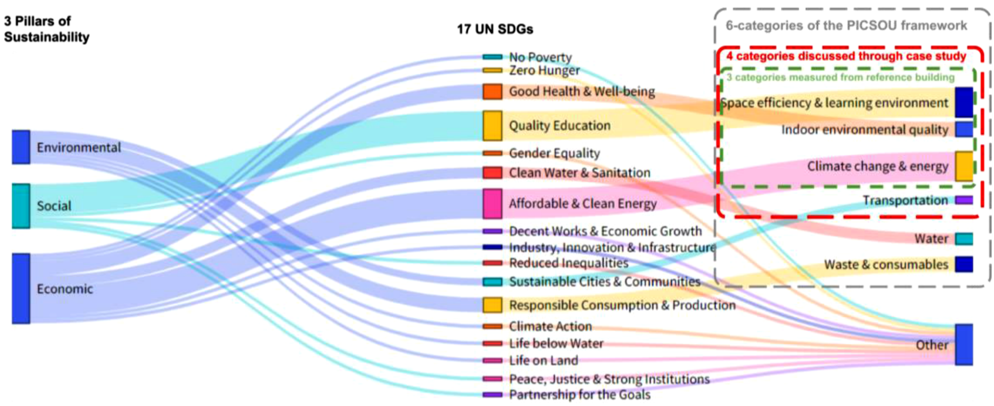


Fig. 5. The correlation between 3 Pillars of Sustainability, 17 Sustainable Development Goals of the UN, and the PICSOU framework.

Table 1
The PICSOU framework.

Sustainability category	Key performance indicators (KPIs)	Data source/update frequency	Target value	TalTech baseline value (result from case study)
1. Space efficiency & learning environment	Auditoriums and other learning spaces measured by m^2 per student	Calculated from campus summary form, updated annually	1.5–2.0 m^2 + 5 m^2 for presentation can be even bigger range, 75% occupancy rate, 56% utilization	1.41 m^2, presentation area usually bigger than 5 m^2, occupancy rate by default is 75%, average utilization rate per classroom/auditorium according to results from U03 building is 29% (U03)
	Teaching laboratory m^2 per student	Calculated from campus summary form, updated annually	4.0–6.0 m^2, 75% occupancy, 38% utilization (for teaching laboratories)	1.76 m^2 (considering all types of laboratories), unable to document actual occupancy and utilization rate of laboratories (18 buildings)
	Office & meeting rooms per staff	Calculated from campus summary form, updated annually	12 m^2	13.4 m^2 (18 buildings)
	Total space per person (staff + students)	Calculated from campus summary form, updated annually	To be specified locally	10.3 m^2 (18 buildings)
	Self-learning and group working spaces (informal learning seats), number of informal seats per formal seat	Calculated from campus summary form, updated annually	0.3 informal learning seats to every formal seat	0.50 m^2 per student, this result only accounts for documented self-learning spaces, informal learning spaces are not documented. Number of informal learning seats not possible to document, nor is its portion to formal learning seats. (18 buildings)
	Sports facility per person (staff + students)	Calculated from campus summary form, updated annually	To be specified locally	1.12 m^2 (18 buildings)
	Ratio of parking space (including underground parking) per person	Documented by asset manager, updated annually	0.05 parking space per person (including students and staff)	0.10 parking space/pers (18 buildings)
2. Indoor environmental quality	Indoor air quality, category I and II spaces,%	Monitored or simulated sub-hourly values and booking schedule, updated monthly	80% category I, 20% category II	54% Category I, 29.5% category II and 16.5% category III (U03)
	General thermal comfort, category I and II spaces,%	Monitored or simulated sub-hourly values and booking schedule, updated monthly	80% category I, 20% category II	0% category I, 25.9% category II, 74.1 category III (U03)
3. Climate change & energy	Carbon footprint, tCO_2/pers. a	Calculated from metered monthly values, updated annually	To be specified locally	1.30 tCO_2/pers. a (18 buildings, includes transportation)
	Electricity use, kWh/pers. a	Calculated from metered monthly values, updated annually	To be specified locally	1045 kWh/pers. a (18 buildings)
	Heating use, kWh/pers. a	Calculated from metered monthly values, updated annually	To be specified locally	1265 kWh/pers. a (18 buildings)
	Primary energy use, kWh/m^2. a	Calculated from metered monthly values, updated annually	To be specified locally	349 kWh/m2, a (18 buildings) calculated with national primary energy factors: 1.0 for natural gas, 0.65 for district heating, and 2.0 for electricity
	Renewable energy export, kWh/(m^2. a)	Metered monthly values, updated annually	To be specified locally	< 1 kWh/(m^2 a)
	Carbon offset, tCO_2/pers. a	Not in practice	To be specified locally	0 tCO_2/pers. a
	Carbon footprint of building materials for new construction and major renovation, $kgCO_2$-eq/m^2	Calculated value from the design documentation for the new construction research building (CON)	To be specified locally	5.86 kg CO_2eq/m^2, a
4. Transportation	Carbon footprint from work trips, business trips (no data), inside campus transport (no data), tCO_2/pers. a	Calculated based on survey statistics, updated annually	To be specified locally	Work trips on average, 0.35 tCO2/pers, a, of which, car commuters (accounts for 31.8% of total campus population) contribute to 75% of total traffic carbon footprint, at 0.84 tCO2/pers, a (18 buildings). *
5. Water	Water use, m^3/pers. a		To be specified locally	Unmeasured - low relevance to local context
	Capacity for stormwater runoff absorbance, m^3/a		To be specified locally	Unmeasured - low relevance to local context
6. Waste & consumables	Recycled waste streams, kg or m^3/pers. a		To be specified locally	Unmeasured - low relevance to local context
	Electronic waste, €/pers. a		To be specified locally	Unmeasured - low relevance to local context
	Organic/food waste, kg/pers. a		To be specified locally	Unmeasured - low relevance to local context
	Toxic waste, m^3/a		To be specified locally	Unmeasured - low relevance to local context

*Current emission value from car commuters does not consider emissions from electrical vehicles due to their low percentage.
By January 2019, electric and hybrid vehicles combined account for 1% of total vehicles registered in Estonia, of which, 1254 were electric.

contribute to a normal energy use pattern of the campus, as one study conducted on 25 campus buildings in the Netherlands clearly demonstrated a significant decrease in both total and specific energy use compared to the pre-pandemic era (Xu et al., Jan., 2023)) from 18 non-residential university buildings with a total net area of 108,312 m^2, these buildings are marked with red abbreviations in Fig. 4.

3. Results and discussion

3.1. PICSOU - the six-category framework

Based on the literature study covered in Section 1.2, we devised a diagnostic tool by identifying a simple six-category framework with minimal number of KPIs designated as PICSOU, - Performance Indicators for Core Sustainability Objectives of Universities for the scientific and continuous measuring of university campus sustainability, whose metrics can facilitate an informed decision-making on the environmental goals (both indoors and emission-wise) or cost-benefit analysis. Under this framework, physical categories directly contributing to carbon footprint such as space efficiency, indoor environmental quality, climate change and energy, transportation, water, waste and consumables are included whereas managerial categories like academics, coordination and planning, investment and finance are omitted. Within the 6 categories, we only conducted in-depth evaluation of the impact of 4 categories over TalTech's Mustamäe campus due to their significant influence on carbon footprint and cost-benefit analysis. Categories that were not studied in depth in this study are of equal importance in terms of their distinctive environmental and economic value, but have rather limited effect on the overall results of the case study. All categories of the framework correspond to relevant SDGs, whose principle is in line with one of the 3Ps according to study by Barbier and Burgess, Oct. (2017) (see Fig. 5). It is worth noting that though each category and their respective KPIs are meant to be general, their improvement measures can always have a local origin.

3.1.1. Space efficiency and learning environment

The first category serves both as an audit of he current space arrangement of the campus as well as a point of interest in discovering the probable correlation between availability and quality of learning space, as decision-makers and users of space often experience things differently (Consensus Statement of the Health Enhancement Research Organization, American College of Occupational & Environmental Medicine & Care Continuum Alliance, 2013). Generalized statistics such as area of auditorim or laboratory per student is commonly measured and compared against capacity criteria listed in university space planning guidelines practiced among higher education institutions (HEIs) located in different climate zones (B. & R. E. Department of Capital Planning & Space Management Land, 2003) (Facilities Services Idaho University, 2009) (Space Management & Planning Unit at Deakin, University) (University Planning Design & Construction Department, 2016), which mainly reference the US Department of Education's Postsecondary Education Facilities Inventory and Classification Manual (Cyros & Korb, 2006), as well as guidelines by organizations such as the Tertiary Education Facilities Management Association, the Higher Education Funding Council of England and Association of Physical Plant Administration (APPA) of North America.

For each type of mapped space use, the space efficiency based on course time table, booking records and cleaning schedule can be a good indicator for the actual quality of learning environment and was calculated using Eq. (9) (Space Management & Planning Unit at Deakin, University):

$$Utilization = Frequency * Occupancy \tag{9}$$

Where:

Frequency equals the percentage of hours a room is booked in a week against a standard academic week of 42.5 h in Estonia, and *Occupancy* equals the number of people in a space over the space's designated capacity.

3.1.2. Indoor environmental quality

Enhanced indoor air quality is positively correlated with improved health, cognitive and physical developoment (Porta et al., 2016), higher incomes and better economic performance (Fisk & Seppanen, 2007). Additionally, the study by Seppänen et al. (O. Seppanen et al., 2006) had documented quantitative relation between temperature and performance, such patter was further tested and confirmed in the study by Lan et al. (Lan et al., 2021). Maintaining suitable indoor climate is a need for the occupants' wellbeing, while requiring very strict thermal comfort conditions and very high levels of indoor air quality in buildings represents also a high expense of energy, with its consequential

Table 2
Campus summary form of TalTech's Mustamäe campus.

NET USABLE AREA (*NUA*):					85.0%					*100%* 115194 m^2 3644 spaces		**15.0%**
NET ASSIGNABLE AREA(NAA):					**56.9%**			*66.9%* 77064.6 m^2 2371 spaces	NON-ASSGNABLE AREA (NASA)	**28.1%**	*33.1%* 38129.4 m^2 1273 spaces	
Percentage by **gross area**	**10.1%**	**1.9%**	**13.1%**	**12.6%**	**3.8%**	**3.6%**	**9.4%**	**0.2%**	**1.8%**	**18.9%**	**7.4%**	
Percentage by *NUA*	*11.9%*	*2.3%*	*14.8%*	*17.9%*	*4.5%*	*4.2%*	*11.0%*	*0.3%*	*2.1%*	*22.3%*	*8.7%*	
Average space size	52.7 m^2	56.8 m^2	35.4 m^2	19.2 m^2	114.7 m^2	107.5 m^2	31.9 m^2	18.7 m^2	5.2 m^2	47.5 m^2	38.2 m^2	
Number of spaces	261	46	481	1077	45	45	396	20	470	540	263	
Space category	CLASSROOMS 13741.9 m^2	GENERAL USE 2614.8 m^2	LABORATORIES 17041.6 m^2	OFFICES 20635.2 m^2	SPECIAL USE 5159.6 m^2	STUDY SPACE 4838.9 m^2	SUPPORT 12659.5 m^2	UNCLASSIFIED 373.7 m^2	BUILDING SERVICES 2433.8 m^2	CIRCULATION 25644.7 m^2	MECHANICAL 10050.9 m^2	STRUCTURAL GROSS AREA 20328.4 m^2
Physical scope: 18 buildings, 94 floor plans; 38 departments												

environmental impact and cost (Corgnati et al., Jun., 2011). This issue is clearly expressed by the Energy Performance of Buildings Directive (EPBD) 2002/92/EC, together with the most recent 2010/31/EU, which underlines that the expression of a judgment about the energy use of a building should be always joint with the corresponding indoor environmental quality level required by occupants to optimize health, indoor air quality and comfort levels. To this aim, the concept of indoor environment categories has been introduced in the EN 16,798–1 standard (European Committee for Standardization (CEN) 2018), and applies to buildings adopting natural ventilation, mechanical ventilation, or a hybrid of both. These categories range from I to III with category I referring to the highest level of indoor climate requirement. Previous study by Seinre et al. (Seinre et al., 2014) suggested 3 indicators for measuring indoor environmental quality's influence on building occupants' productivity, covering indoor air quality, for which outdoor air ventilation rate is used as a proxy, and general thermal comfort, independent of active or passive system type, which are:

3.1.2.1. Ventilation rate – productivity. Ventilation rate's affect over productivity had been studied in depth by Seppanen et al. (O. Seppanen et al., 2006) and documented in the Federation of European Heating, Ventilation and Air Conditioning Associations (REHVA) Guidebook (Wargocki et al., 2006), whose polynomial expression can be approximated as:

$$P_V = -0.00002L^2 + 0.0019L + 0.9901 \tag{10}$$

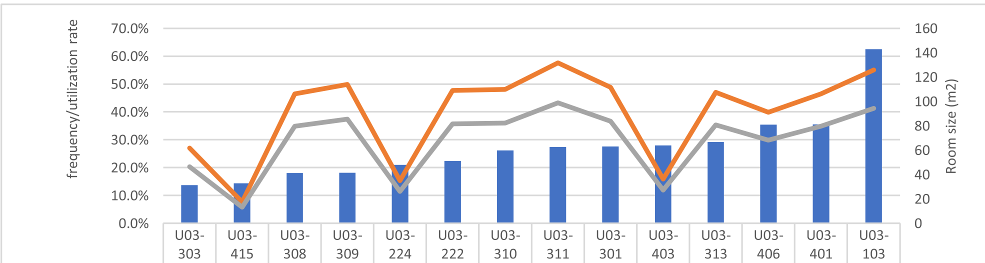
Where *Pv* is a dimensionless quantity for the relative performance in relation to a set ventilation rate of 6.5 L/s, pers and *L* is ventilation rate measured in L/s, pers.

3.1.2.2. Ventilation rate – sick leave prevalence. The ventilation rate's affect was studied by many, among which, the office buildings discussed by Fisk et al. (Fisk et al., 2003) and Milton et al. (Milton et al., 2000) were the most appropriate building type to be used for university campus buildings. Such affect can be approximated as:

$$SL = -0.0294ACH^3 + 0.2709ACH^2 - 0.8209ACH + 0.9611 \tag{11}$$

Where *SL* is a dimensionless quantity for sick leave prevalence relative to that with no ventilation and *ACH* is the hourly air change rate measured in 1/h. For a given scenario where the floor height and area of a room are defined, *SL* reaches its minimum (optimal) value of 0.0109 around the *ACH* of 4.8 h^{-1}, any *ACH* above this value will result in a negative *SL* value, which does not reflect reality. This means Eq. (11) can only realistically approximate the *SL* value when *ACH* <= 4.8 h^{-1}.

3.1.2.3. Indoor temperature – productivity. We calculated temperature's effect over productivity using the equation obtained in the study by Seppanen et al. (O. Seppanen et al., 2006):



	U03-303	U03-415	U03-308	U03-309	U03-224	U03-222	U03-310	U03-311	U03-301	U03-403	U03-313	U03-406	U03-401	U03-103
size (m2)	31.23	32.8	41.21	41.44	48	51.1	59.71	62.56	63.1	63.9	66.7	81	81.1	142.84
frequency	27.1%	7.6%	46.5%	49.9%	15.3%	47.6%	48.0%	57.6%	48.8%	15.9%	47.1%	39.8%	46.5%	55.1%
utilization	20.3%	5.7%	34.9%	37.4%	11.5%	35.7%	36.0%	43.2%	36.6%	11.9%	35.3%	29.9%	34.9%	41.3%

Fig. 6. Learning space utilization in Building U03 (calculated using Eq. (9) Occupancy was assigned a default value of 75%, resulting in a clear linear correlation between Frequency and Utilization in the plotted chart).

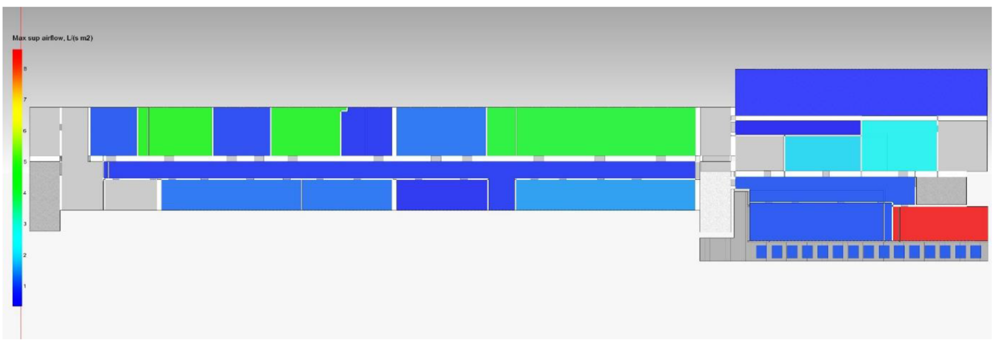


Fig. 7. Map of maximum supply air flow on Floor 2 of the U03 building based on IDA ICE model featuring the pre-renovation condition.

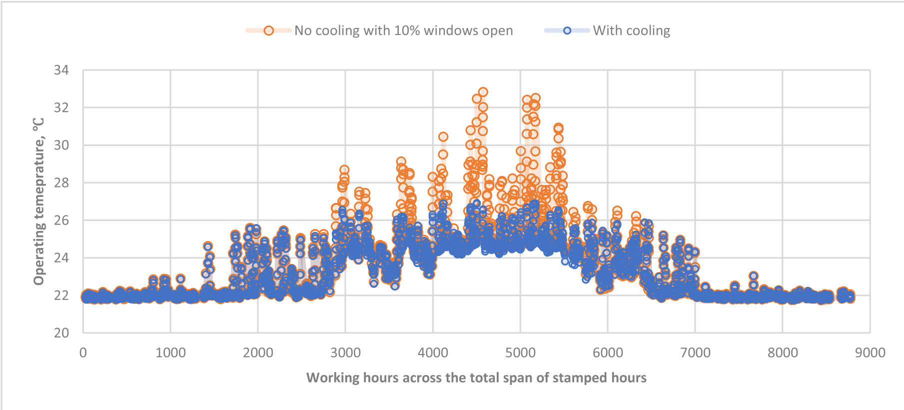


Fig. 8. Reference room's distribution of operating temperatures under both cooling scenarios.

$$P_T = 0.1647524T - 0.0058274T^2 + 0.0000623T^3 - 0.4685323 \quad (12)$$

In which, P_T is a dimensionless quantity for the productivity relative to maximum its maximum value, whereas T indicates temperature measured in Celsius (°C).

3.1.2.4. Combined productivity. We calculated the combined productivity by solving for the arithmetic sum of the net increase/decrease of productivity due to increased ventilation rate compared to the reference ventilation rate *Pv*-1, operating temperature compared to optimal temperature P_T-1, as well as avoided sick leave (by default, sick leaves consist 2% of total annual working hours, therefore increased productivity from avoided sick leaves can be expressed as 0.02 – 0.02*SL*.) The per person Productivity Increase was calculated as:

$$Productivity\ Increase = (P_V - 1) + (P_T - 1) + 0.02*(1 - SL) \quad (13)$$

Under a test scenario where $L = 10$ L/s, pers and cooling period $T = 24$ °C, Eq. (13) yielded a value of 0.01708, indicating that the productivity is about 1.7% higher than the reference value (for which, Eq. (13) is expected to yield a value of 0), and is thus considered a more preferable indoor climate scenario. To monetize this increased productivity, we assumed that a university staff is a typical office worker, whose hourly wage is twice the Estonian average (Statistics Estonia, 2021), and works 8 h a day, 5 days a week, 250 days a year. A 1.7% increase in productivity will amount to approximately 618.8 €/pers, a of increased gross income as a result of improved indoor climate.

3.1.3. Climate change and energy

Since energy use such as heating and electricity are commonly metered in buildings, it is possible to measure Scope 1 and Scope 2 CO_2 emissions by applying typical local emission factors. For Tallinn, such numbers are 0.11 tCO_2eq/kWh for district heating and 0.717 tCO_2eq/kWh for average emissions from production of electricity (Ministry of the Environment of Republic of Estonia, 2021), we also used these values in Eq. (8) to calculate *Unit Area Carbon Reduction*. For new construction, carbon footprint of building materials should be also measured using the LCA (Life Cycle Assessment) method, as recent research indicates that the benefit of decarbonization of building materials can be as significant as 20% in carbon footprint reduction in a materials-neutral manner (Ministry of Environment Finland, 2021).

3.1.4. Transportation

This category addresses Scope 3 CO_2 emissions incurred from

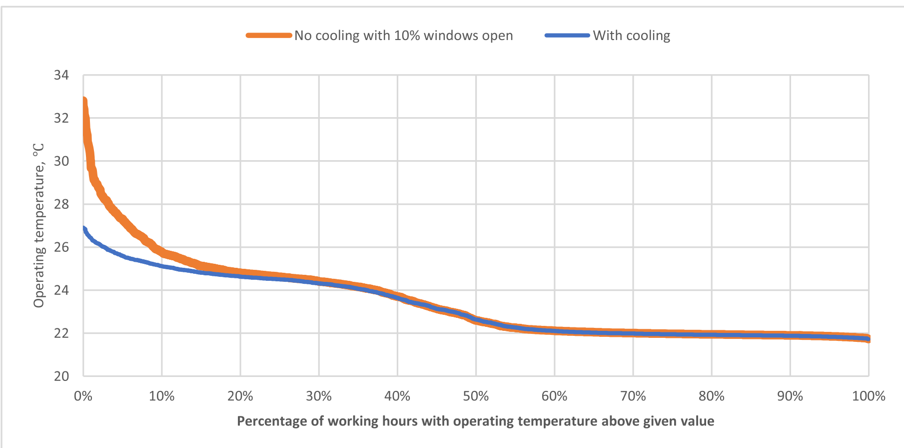


Fig. 9. Reference room's duration curve of operating temperatures under both cooling scenarios.

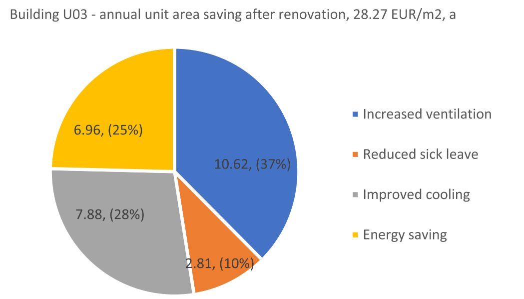


Fig. 10. Breakdown of the U03 building's post-renovation annual unit area monetary benefit.

transportation, including commuting to and from the TalTech campus, work trips, business trips. Mapping of transportation-related emissions on campus helps identify major contributor(s) of CO_2 emissions and thus provides a solid evidential basis for adjustment in policy making as well as planning of transit nodes and dormitories within and around the campus, as most people prefer to walk no more than 400 m or five minutes to casual destinations and no more than 800 m for regular trips such as daily commute (Associates & Law, 2008).

3.1.5. Water

Although water consumption generates negligible (about 1%) CO_2 emissions compared to that incurred from a building's operation and its associated transportation (Seinre et al., 2014), water as a necessity for sustaining human livelihood is threatened by imbalanced distribution, massive pollution and vast shortage in many parts of the world and sustainable use of water is ranked as one of the most crucial SDGs – same reason water efficiency is emphasized by all major green building rating systems. Prevention of local water body pollution from stormwater runoff is also considered by the PICSOU framework, in which, stormwater runoff absorbance capacity of a site can be calculated using the Small Storm Hydraulic Method (Pitt, 1999), this value can facilitate the planning of vegetated area against urban heat island effect and ground water contamination.

3.1.6. Waste and consumables

Similar to KPI Category 5, this category has rather limited contribution to the overall CO_2 emissions of a university campus given the fact that the waste sector's emission (including but not limited to the emission from wastewater treatment and discharge mentioned in the previous category) consists only 2.4% of total emissions in Estonia in 2021 and is projected to be 1.9% by 2050 (Ministry of the Environment of Republic of Estonia, 2021) thanks to detailed EU waste regulation. However, pollutants and GHG released from waste materials that are improperly sorted, recycled, and disposed usually result in catastrophic ecological consequences while causing massive waste in energy and virgin materials as well as depriving considerable size of land and funding for treatment, in the EU, about 25% of the total waste stream consists of construction and demolition waste (Arcadis, BIO INtelligence Service, 2013). Such rationale justifies the necessity of including the mapping of major waste stream and their carbon footprint in the KPI categories, without which, a genuinely sustainable campus objective will be obsolete and inadequate.

3.1.7. KPIs of each PICSOU category

A summary of PICSOU categories and their KPIs, as well as each KPI's

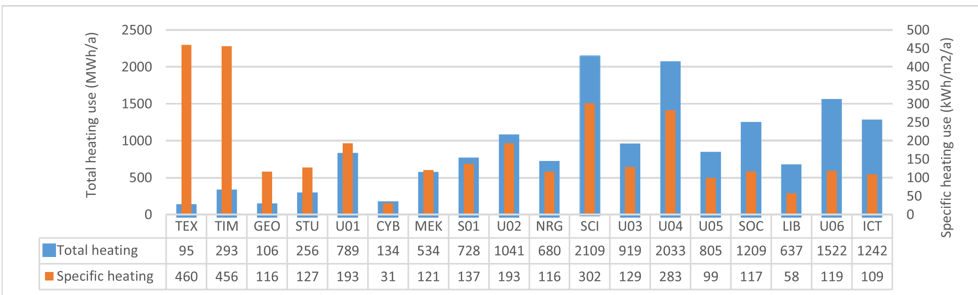


Fig. 11. Total and specific heating use of selected campus buildings.

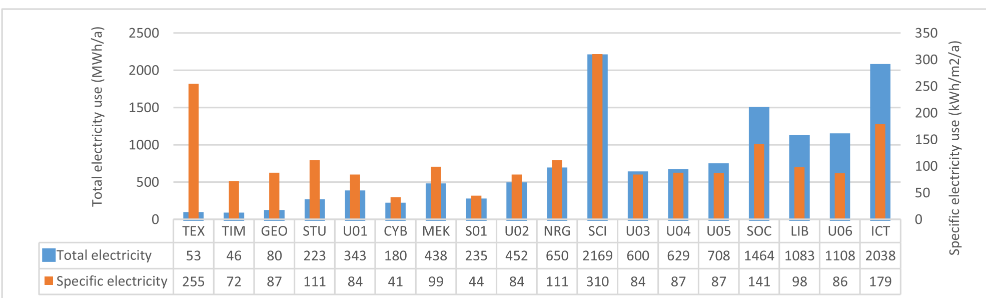


Fig. 12. Total and specific electricity use of selected campus buildings.

target value are listed in Table 1. For the first 4 categories, results from the case study on TalTech's Mustamäe campus were also measured, categories 5 and 6 were not considered for this study due to their low local relevance. Category numbers corresponding to the ones listed in Table 1 (numbered 1 through 4) can be also found in the superscript of building abbreviations in Fig. 4, denoting the categories whose KPIs were directly contributed by the building's data.

3.2. Case study

Though PICSOU's categories and KPIs have generic nature, which enables the framework to be applied to other campuses as well, KPIs' target values have to be specified locally. Out of 23 KPIs under 6 categories, we were able to successfully measure 16 KPIs from the first 4 categories on TalTech's Mustamäe campus.

3.2.1. Space efficiency

3.2.1.1. Mapping of spaces on campus. In order to measure space efficiency, we created a campus summary form to document the per-person area of each space type across 18 campus buildings (see Table 2).

It can be observed from Table 2 that, while all other space types have a reasonable average space size, the average space size of study space is abnormally big (107.5 m^2), which does not reflect reality. This is due to

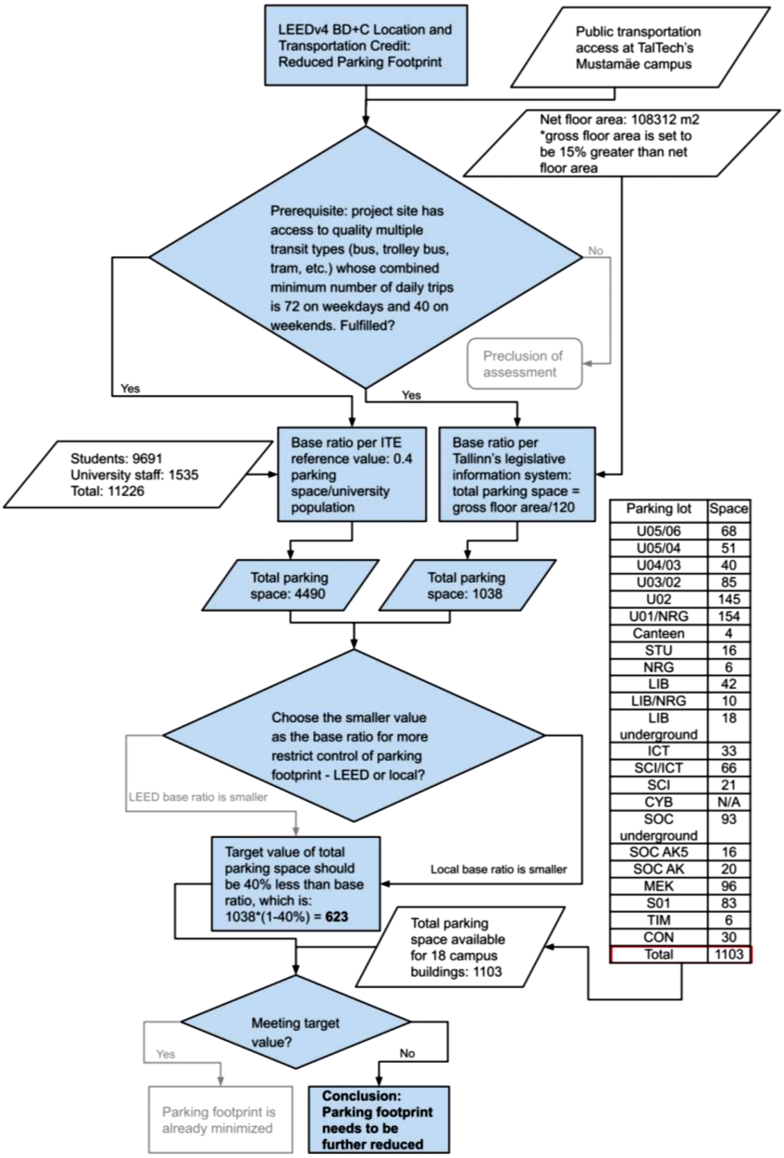
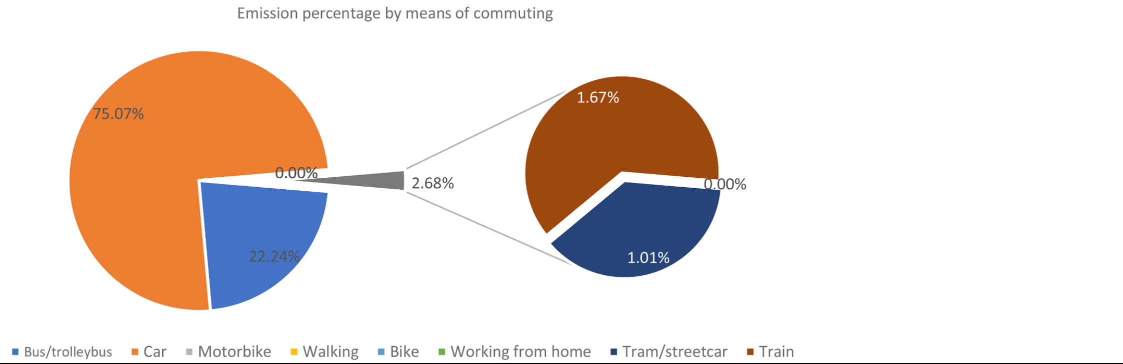


Fig. 13. Workflow for deciding parking space target value. Major steps followed in this flowchart are highlighted using color-filled shapes.

Table 3
Overview of Mustamäe campus' transportation-related CO_2 emissions.

Means of commuting	Percentage %	Calculation assumptions	Number of commuters	Annual CO_2 emissions tCO_2
Bus/trolleybus	36.36	20 g of CO_2 per minute for each passenger, daily one-way commuting time is 21.66 min, 250 working days annually	4082	884.1
Car	31.82	132.4 g of CO_2 per km, daily one-way commuting distance is 12.62 km, 250 working days annually	3572	2984.3
Motorbike	0	80 g of CO_2 per minute, 250 working days annually	N/A	N/A
Walking	21.59	N/A	2424	0
Bike	4.55	N/A	511	0
Working from home	2.27	N/A	255	0
Tram/streetcar	2.27	15 g of CO_2 per minute for each passenger, daily one-way commuting time is 21 min, 250 working days annually	255	40.1
Train	1.14	10 g of CO_2 per minute for each passenger, daily one-way commuting time is 104 min, 250 working days annually	128	66.6
Overview ⇓		**Total ➡**	**11,226**	**3975**



the fact that most formal study spaces are available in the library, where reading halls can have exceptionally ample space (for example, room 222 in the library has an area of 1137.3 m^2) while group study spaces are usually sized around 10 m^2 and individual study spaces less than 3 m^2.

3.2.1.2. Utilization of classrooms. Mapping the learning space utilization helps streamline the maintenance activity and minimize the operational costs/emissions by identifying under-occupied learning spaces. As an example, in this case study, the utilization rate of classrooms in building U03 was calculated using Eq. (9) (Space Management & Planning Unit at Deakin, University). To do that, we singled out all rooms in U03 fitting the classroom category in Table 2 from the university room register system, and accessed each classroom's booking schedule in the study information system to calculate their weekly booked hours, and eventually yielded the *Utilization* (see Fig. 6).

3.2.2. Indoor environmental quality

3.2.2.1. Monetary benefits. Investments in energy efficiency are not an attractive investment for landlords from an economic perspective (März et al., 2022). This study helps building owners look beyond the common practice of simple payback model of renovation by quantifying also the benefit from improved indoor environmental quality, in addition to return in energy saving.

We took U03 as a reference building, which has 61 rooms (auditoriums, offices, laboratories) across its four-story premises totaling 6482 m^2 of NUA. We calculated each room's capacity, ventilation rate (L/s, pers), air change rate (1/h) and indoor environmental category, and solved the current *Pv* value and *SL* value of each room using Eq. (10) and Eq. (11). We also calculated each room's would-be post-renovation *Pv-SL* value set by assigning the optimal air supply rate and ventilation rate. We then used the difference in each room's pre and post renovation *Pv-SL* value set in Eq. (4) to yield the total quantified annual productivity increase from increased ventilation and reduced sick leave prevalence.

Similarly, in order to solve for the productivity increase from increased cooling using Eq. (12) and Eq. (4), we adopted an IDA ICE model of U03 (see Fig. 7). The IDA ICE model had 2 simulation scenarios, "no mechanical cooling with 10% windows open" was used to imitate the pre-renovation condition, and "with mechanical cooling" the post-renovation.

The simulation results exhibited clear discrepancy between the 2 scenarios, indicating that the post-renovation operating temperature is significantly lower than that of pre-renovation during the warmest months of a year (see Fig. 8) with a narrower range of temperature fluctuation (see Fig. 9).

We then calculated the total quantified productivity increase from all improvements in the indoor environmental quality (increased air change rate, reduced sick leave prevalence, increased cooling), and divided this value by the total net area of U03 to yield the annual unit area productivity increase. Fig. 10 features a breakdown of the annual unit area saving after renovation, which shows that saving from productivity increase due to improved indoor environmental quality contributes remarkably greater than energy saving. The renovation corresponded to deep renovation recommended in Estonia's long-term renovation strategy (Ministry of Economic Affairs & Communications of Estonia & Tallinn University of Technology, 2020) with a unit area cost of 600 €/m^2, by substituting this value together with the post-renovation annual unit area benefit into Eq. (1), we yielded a simple payback time of 39 years, a more favorable payback time compared to an 86-year simple payback time considering only energy saving.

Table 4
Carbon footprint/cost of PICSOU categories calculated from Mustamäe campus' baseline values and optimal values.

Sustainability category	Carbon footprint/cost based on baseline values	Carbon footprint/cost based on optimal values	Impact
1. Space efficiency & learning environment	Assumptions: 1 Total auditorium area unchanged; 2 Specific heating/energy use across all buildings based on building-specific real-life value. Carbon footprint: 10,626 tCO_2eq/a	Assumptions: 1 Total auditorium area reduced by 25% (so that default occupancy becomes 100%) to maximize space utilization; 2 All reduced auditorium area heated by district heating. Carbon footprint: 10,289 tCO_2eq/a	Annual carbon footprint reduction by 337 tons (3.2%)
2. Indoor environmental quality	Assumption: Actual situation in offices and laboratories. Total productivity increase: 0 EUR/a	Assumption: Post-renovation productivity increase applies to staffed laboratories and all offices. Total productivity increase: 439,737 EUR/a	Annual monetary benefit: 439,737 EUR (equivalent to 17.6% of pre-renovation total energy cost in PICSOU category 3)
3. Climate change & energy	Assumption: Actual situation in all buildings. Total energy cost: 2,498,480 EUR/a; Carbon footprint: 10,626 tCO_2eq/a.	Assumptions: 1 All buildings heated by district heating; 2 Post-renovation energy saving and carbon footprint reduction apply to all buildings; 3. Specific heating/energy use across all buildings based on lowest real-life value.Total energy cost: 754,501 EUR/a;Carbon footprint: 3353 tCO_2eq/a.	Annual energy saving by 1,743,979 EUR (69.8%); Annual carbon footprint reduction by 7273 tons (68.4%).
4. Transportation	Assumptions: 1 distribution of means of commuting unchanged; 2 Ratio of parking space unchanged. Carbon footprint: 3975 tCO_2eq/a	Assumption: Number of car commuters reduced by the same number as reduced parking spaces, reduced number proportionally redistributed to other means of commuting. Carbon footprint: 3636 tCO_2eq/a	Annual carbon footprint reduction by 339 tons (8.5%)
5. Water	Assumption: No additional water saving features implemented, thus no contribution to carbon footprint reduction from sewage water treatment.	Assumption: Additional water saving features implemented, consequently contributes to carbon footprint reduction from sewage water treatment.	Neglectable
6. Waste & consumables	Assumption: No measures taken to reduce creation of certain waste flow(s) at source, thus no contribution to carbon footprint reduction from embedded carbon footprint of virgin materials and treatment of their waste.	Assumption: Measures taken to reduce creation of certain waste flow (s) at source, consequently contribute to carbon footprint reduction from embedded carbon footprint of virgin materials and treatment of their waste.	Neglectable

Table 5
Comparison of characteristics between the PICSOU framework (highlighted in bold texts) and other existing tools.

	PICSOU	UNSDG	LEEDv4.1 OM/EB	BREEAM In-Use International 2015	UI GreenMetric
Composition	**6 categories, 23 indicators, no scorecard**	17 goals, 169 targets, no scorecard	10 categories, 27 credits, scorecard with max. 110 points	9 categories, 209 indicators, scorecard with max. 100%	6 categories, 51 indicators, scorecard with max. 10,000 points
Purpose	**Framework for monitoring sustainability performance**	List of sustainability challenges	Standard for green building certification	Standard for green building certification	Technical reference for participating global ranking of sustainable universities
Specifically for university campuses?	**Y**	N	N	N	Y

3.2.2.2. Environmental benefits. We calculated the cost effectiveness for U03's renovation using Eqs. (6), (7) and (8), and yielded an MAC value of −1160 €/tCO_2eq, m^2. Though the negative MAC value shows that investing in carbon reduction does not directly benefit the building owner financially, considering the profound environmental impact of carbon reduction, early investment is still preferable.

3.2.3. Climate change and energy

We calculated the total and specific heating and electricity use of 18 campus buildings based on a 3-year average between 2017 and 2019, and plotted this data in Figs. 11 and 12, in which, buildings were arranged in an ascending order of total area. On average, buildings on the Mustamäe campus used 176 kWh/m^2, a for heating and 115 kWh/m^2, a for electricity.

3.2.4. Transportation

3.2.4.1. Ratio of parking space. To do that, we adopted the method used by the LEEDv4 BD+C (Building Design and Construction) rating system (U.S. Green, 2019) and picked the smaller value between the compliant number set by ITE (the U.S. Institute of Transportation Engineers) (Meyer, 2009) and the one set by the local regulation in Tallinn (Terik, 2020) as the reference value for parking footprint reduction (see Fig. 13). Although LEEDv4 BD+C is meant mainly for new constructions instead of existing buildings, it provides a good workflow for calculating the would-be number of parking spaces at a university campus.

3.2.4.2. Transportation-related carbon footprint. In this study, we were able to calculate work trip related emissions from car, bus/trolleybus,

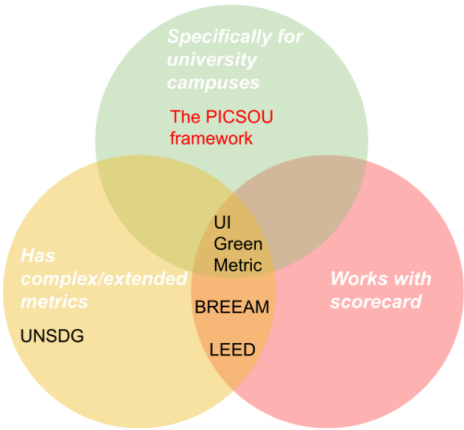


Fig. 14. The relation between the PICSOU framework and existing tools.

tram/streetcar, and train. Although emissions from business trips and on-campus transportation are also considered relevant transportation-related emissions in the PISCOU framework, due to lack of information, they were not calculated in this study.

At 132.4 gCO_2/km, Estonia's average passenger car emission is prominently higher than the EU value of 120.8 gCO_2/km in 2018 (Pastorello et al., 2020), reducing commuting car use helps minimize one of the biggest contributors to TalTech's transportation carbon footprint. To determine the daily number of cars commuting to the Mustamäe campus, we applied the overall percentage of means of transportation and calculation assumptions based on an online survey about the city of Tallinn ("Traffic in Tallinn, Estonia", 2021) to the total university population, and also yielded each means of transportation's respective carbon footprint (see Table 3).

3.2.5. Impact assessment

Based on the case study, we calculated the carbon footprint/monetary saving of different categories based on both baseline value and optimal value (see Table 4). Considerable savings achieved revealed the importance of selected categories and illustrated their respective impact.

4. Conclusions

4.1. Findings

Inspired by the UNSDGs and reflecting on the popular green building certification systems and university rankings, we identified a minimum number of categories and indicators for the PICSOU framework (see Table 5).

It was our objective to identify a minimalistic framework that is unique in a way that it is meant specifically for university campuses and does not rely on complex/extended metrics contributing to a scorecard to showcase a campus' level/ranking of sustainable development (see Fig. 14). Instead, the framework monitors the real-time sustainability performance of a campus to guide customizable improvements.

We tested the PICSOU framework on TalTech's Mustamäe campus and came up with the following findings:

1 In reference building U03, the highest *Utilization* (43%) was notably lower than the target value (56%) with several classrooms having exceptionally low *Utilization* (close to 10%), this pattern can be expected from other campus buildings with similar floor plan and functions. Such result contradicts a current belief that the campus needs expansion to accommodate a greater research/teaching capacity and opens up opportunity for further reducing the operational emissions/cost.

Table 6
Qualitative cost-benefit breakdown of improvement measures for TalTech's Mustamäe campus.

Sustainability category	Improvement measure	Applicability	Cost category	Benefit category
Space efficiency & learning environment	1. Increase area of over-utilized spaces 2. Reduce area of/convert under-utilized spaces 3. Rearrangement of spaces 4. Release unnecessary spaces 5. Create new spaces if proven necessary	generic building-specific generic generic generic	Renovation cost, Remodelling cost, Lease cost, Construction cost	Improved learning performance, Increased productivity, Improved wellbeing
Indoor environmental quality	1. Increase ventilation rate 2. Improve air-conditioning 3. Improve daylight and artificial lighting 4. Procure low-emitting furniture/interiors	building-specific building-specific generic generic	Retrofit investment, Procurement/installation cost for interiors	Increased productivity, Reduced sick leave, Improved indoor air quality
Climate change & energy	1. Install passive/active solar systems 2. Use/produce green energy 3. Eliminate refrigerants or use low-impact refrigerants 4. Energy renovation (combined with IEQ improvement) 5. Establish target value of building materials' carbon footprint for new build design and procure construction materials meeting recognized disclosure criteria such as ISO 14,025 and EN 15,804	generic generic generic building-specific generic	Retrofit investment, Renewable energy certificate (REC) procurement cost, Material cost, Carbon offset investment	Reduced carbon footprint, Reduced energy cost, Improved energy efficiency, Minimized solid waste and pollution
Transportation	1. Promote commuting with public transportation/biking/walking through incentive programs 2. Install biker-friendly facilities 3. Diversify amenities within walking distance 4. Subsidize green vehicle use 5. Install electric vehicle supply equipment (EVSE)/dedicate parking space for electrical vehicles	generic generic generic generic generic	Promotion campaign cost, Procurement/installation cost for biking facilities/ EVSE, Monetary/flexible schedule incentives, Energy subsidy for electrical vehicles	Reduced carbon footprint, Minimized traffic air pollution, Enhanced community engagement

2 The campus' current parking footprint needs to be reduced by 43.5%, or down to 0.05 parking space/university population to minimize its land consumption, automobile dependence, car-related emissions and rainwater runoff.
3 The huge discrepancy in simple payback time (39 years vs. 86 years) verified the necessity to consider co-benefits in parallel to energy saving and carbon reduction, thanks to which, increased ventilation/cooling and higher energy efficiency (and consequently reduced carbon footprint) can be all achieved at the same time.
4 The campus' transportation emission breakdown indicated a clear and disproportionate domination of car emissions (car commuters account for less than one-third of total commuters but contribute to 75% of total transportation emissions).
5 Depending on local context, categories with presumably high impact such as the "water" category and the "waste and consumables" category can have less impact compared to other categories.

4.2. Suggestions for policy-making

Based on the discrepancy shown in Table 4, we concluded guidelines for possible improvements for the Mustamäe campus using a qualitative cost-benefit breakdown of relevant PISCOU categories (see Table 6).

4.3. Limitations and future studies

1 KPIs under the "space efficiency and learning environment" category may be non-conclusive to measure learning environment quality and require further development.
2 The sample size of the survey used for mapping the campus' composition of transportation-related carbon footprint was small, which might jeopardize the accuracy of the summary of the distribution of means of transportation.
3 The studied campus buildings did not include residential buildings, a unique building type that consists a fair portion of the campus' total building stock, which could undermine the accuracy and reliability of the energy use and carbon footpint results in this study.
4 Even for the 4 PICSOU categories that are relevant to the local context, many of their target values were not decided due to absence of data, which gives rise to two seemingly contradictory interpretations: (1) hard-to-measure KPIs should be replaced by more intuitive easy-to-measure indicators; (2) hard-to-measure KPIs should not be replaced or omitted as they are the justitification of future studies.
5 Only one case study on one campus was conducted in this paper, whose result was in favor of the suggested compatibility of the PICSOU framework. However, it is evident that further case studies need to be conducted on campuses located in different climate zones.

In conclusion, this study provides an unprecedented work from an atypical angle combining both conventional and unconventional metrics, and proposes a promising minimalistic framework that aims to be practical and scalable for other university campuses. With the PICSOU framework, sustainability could be made transparent and monitored in a robust fashion to help university managerial personnels focus on improving areas with he highest impact. Future studies addressing the above-mentioned limitations are expected to complement the framework in its universality.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Comprehensive Workflow for Documenting Corporate Commuting Emissions: A University Case Study with Two Alternative Approaches

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Abstract. As concerns about climate change grow, organizations are increasingly focusing on documenting and reducing their environmental impact, including corporate commuting emissions. This paper presents a comprehensive workflow for documenting corporate commuting emissions within a university context, utilizing two alternative approaches. The study aims to propose effective strategies for emissions reduction through a case study conducted at the Mustamäe Campus of Tallinn University of Technology (TalTech). The objectives include developing a structured framework for data collection, analysis, and emissions calculation, and comparing the two approaches. The conventional approach relies on historical data and surveys, while the novel approach incorporates Telia Crowd Insight and Fyma camera data. The workflow encompasses data acquisition, processing/analysis, and emissions calculation. The results demonstrate significant differences in the calculated commuting emissions between the two approaches. The discussion highlights the transparency and validation challenges associated with the novel approach. The findings suggest the conventional approach for central locations with accessible survey statistics and the novel approach for locations outside the city center. The study contributes to sustainable transportation strategies and offers practical insights for organizations seeking to document and manage their commuting emissions.

Keywords: Commuting carbon emissions · Telia Crowd Insight · Fyma · University campus · Traffic · Transportation

1 Introduction

1.1 Background and Rationale

As the global concern for climate change intensifies, it becomes imperative for organizations to address their environmental impact, including the emissions generated by commuting activities, as transportation generates 14% of global GHG emissions [1]. Corporate commuting emissions, resulting from employees and stakeholders traveling to and

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from their workplaces, contribute significantly to greenhouse gas emissions and air pollution [2]. Recognizing the need for sustainable transportation solutions, organizations are increasingly focusing on measuring, managing, and reducing these emissions.

In the context of corporate sustainability, universities are essential institutions that play a pivotal role in fostering environmental consciousness [3]. As centers of knowledge, research, and innovation, universities have the opportunity to lead by example and develop comprehensive workflows for documenting corporate commuting emissions. By conducting a case study within a university setting, we aim to explore 2 alternative approaches to measuring and documenting commuting emissions and provide insights into effective strategies for emissions reduction.

1.2 Objective and Scope

The objectives of this study are twofold: first, to propose a comprehensive workflow for documenting corporate commuting emissions using 2 alternative approaches, and second, to compare and analyze 2 alternative approaches within a university case study. The workflow encompasses data collection, analysis, and emissions calculation methodologies, providing a structured framework for organizations to understand and manage their commuting emissions. The case study was conducted within a specific physical boundary, the Mustamäe campus of Tallinn University of Technology (TalTech), examining the commuting patterns and emissions of its employees, students and staff.

The scope of this research is limited to the university environment, targeting employees, students, and staff as the primary commuting population. The study encompasses a specific time frame – the year of 2022, during which, for one of the alternative approaches, data on commuting behaviour and modes of transportation was collected and their associated emissions calculated and analyzed. By narrowing the scope to a university case study, we aim to provide practical insights and recommendations that can be adapted by other organizations interested in implementing similar workflows.

2 Introduction

2.1 Two Alternative Approaches

We used 2 alternative approaches to calculate the same type of carbon emissions of the same physical location within the same time window, the former adopted a conventional workflow based on historical data and a 3-year-average survey statistics, which had been used for calculating the commuting carbon emissions of TalTech's Mustamäe campus under a wider university campus sustainability monitoring scheme known as the PICSOU framework [4], the latter adopted a novel workflow which utilized 2 weighted sources of legally collected anonymous traffic data using unique ICT-based algorithms known as Telia Crowd Insight [5] and Fyma [6], commuting emissions converted from such data had been documented in TalTech's 2022 GHG inventory [7]. Figure 1 below sums up the two alternative approaches in terms of their respective working principles and data workflow.

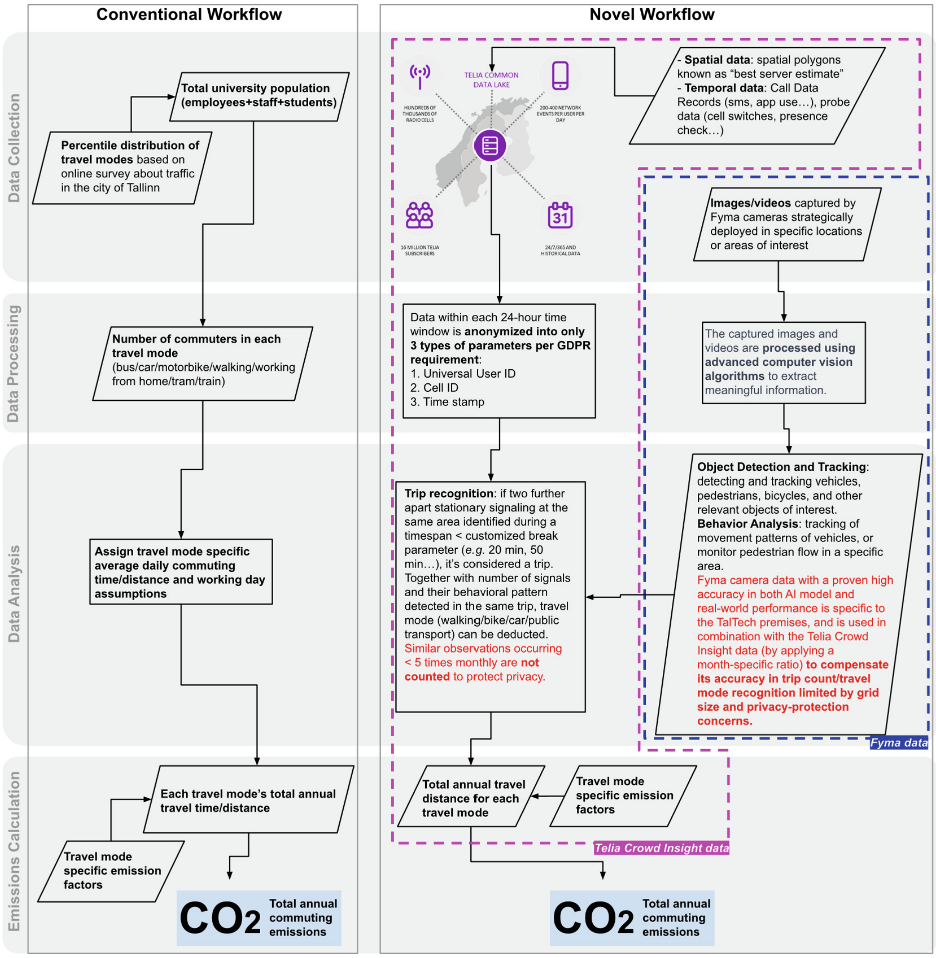

Fig. 1. Working principles and data workflow of 2 alternative approaches

2.2 Two Alternative Approaches

With the conventional workflow, we utilized the percentage of each mode of commuting acquired from an online survey on the distribution of commuting modes in the city of Tallinn [8] as shown in Fig. 2.

With the novel workflow, we utilized Telia Crowd Insight's interactive dashboard which enables custimization of collected data sets in terms of observation time window, range of commuting distance and maximum number of sampled routes as shown in Fig. 3.

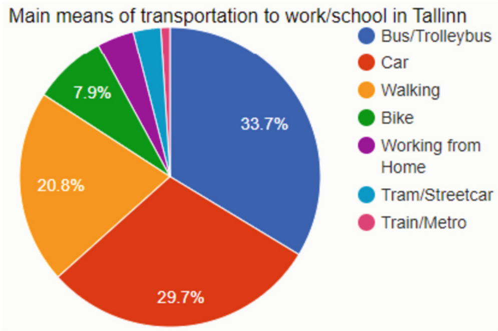

Fig. 2. Distribution of commuting modes in the city of Tallinn based on the 3-year-average of an ongoing online survey

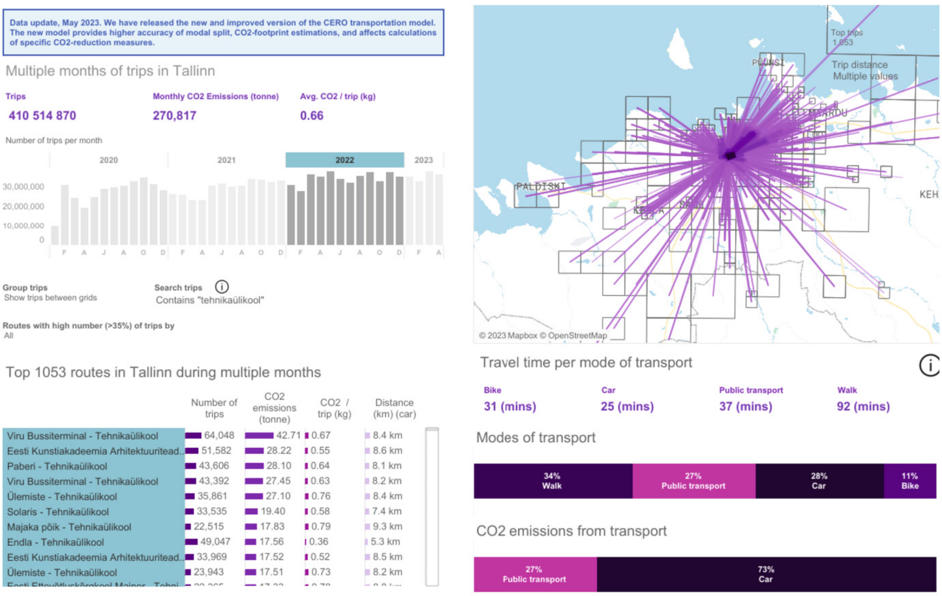

Fig. 3. Screenshot of a customized Telia Crowd Insight dashboard

2.3 Data Processing and Analysis

With the conventional workflow, we considered the total university population of employees, students and staff as the total commuting population, and multiplied it with its corresponding percentage in the overall distribution of commuting modes, this yielded the number of persons using each mode of commuting to and from the campus. Then we applied unique assumption to each mode of commuting based on the same survey statistics in terms of average daily commuting time, average daily distance of travel (one-way) and default annual working days, multiplying such data with the number of persons using the corresponding commuting mode yielded the commuting mode's annual total commuting distance or time (depending on the mode of commuting).

With the novel workflow, we first applied a serie of filters in Telia Crowd Insight's dashboard and yielded the respective total distance traveled using private car, public transport (mode unspecified) and walking. Due to the unique working pinciples of Telia Crowd Insight, such data had to be normalized with the Fyma camera data, which separates the commuting trips to and from the campus from the ones passing by the campus. A travel distance acquired using Telia Crowd Insight and normalized using Fyma data is considered the optimal analogue closest to the actual commuting activity.

2.4 Calculation of Commuting Emissions

The general equation for calculating carbon emissions from commuting can vary depending on the specific factors considered. However, a commonly used equation can be described using Eq. 1:

$$E = \Sigma E_i \tag{1}$$

where E is the total carbon emissions, Ei is the carbon emissions for each mode of commuting which can be expressed using Eq. 2:

$$E_i = D_i \times EF_i \tag{2}$$

where Di is the distance (km) or time (min) traveled (depending on the workflow) and EFi is the carbon emissions factor for the commuting mode.

2.5 Reference Campus

In this study, we used TalTech's main campus – the Mustamäe Campus as the reference campus, and considered the term "university population" as the sum of all employees, students and staff on this campus, totaling 11226 persons.

3 Results

3.1 Commuting Emissions Calculated Using the Conventional Approach

We applied the conventional approach and obtained the following result in Table 1, for which, based on the given calculation assumptions, the total annual commuting emissions of the Mustamäe Campus in 2022 was 3975 tons.

Table 1. Overview of Mustamäe Campus' commuting emissions in 2022 based on the conventional approach

Means of commuting	Percentage %	Calculation assumptions	Number of commuters	Annual emissions tCO2
Bus/trolley bus	36.36	20 g of CO2 per minute for each passenger, daily one-way commuting time is 21.66 min, 250 working days annually	4082	884.1
Car	31.82	132.4 g of CO2 per km, daily one-way commuting distance is 12.62 km, 250 working days annually	3572	2984.3
Motorbike	0	80g of CO2 per minute, 250 working days annually	N/A	N/A
Walking	21.59	N/A	2424	0
Bike	4.55	N/A	511	0
Working from home	2.27	N/A	255	0
Tram/streetcar	2.27	15g of CO2 per minute for each passenger, daily one-way commuting time is 21 min, 250 working days annually	255	40.1
Train	1.14	10g of CO2 per minute for each passenger, daily one-way commuting time is 104 min, 250 working days annually	128	66.6
Total ➡			11226	3975

3.2 Commuting Emissions Calculated Using the Novel Approach

We applied the novel approach and obtained the following result in Table 2, for which, based on the documented activity data and chosen emission factors, the total annual commuting emissions of the Mustamäe Campus in 2022 was 1444 tons.

Table 2. Overview of Mustamäe Campus' commuting emissions in 2022 based on the novel approach

Means of commuting	Annual activity data	Unit	Emission factor	Unit	Annual emissions, tCO2
Passenger car	11760009	passenger-km	0.149	kgCO2e/passenger-km	1414
General public transportation	4204780	passenger-km	0.009	kgCO2e/passenger-km	30
Two-wheeled vehicles	3294696	km	0	kgCO2e/km	0
Walking	364687	km	0	kgCO2e/km	0
Total ➡					1444

4 Discussion

4.1 Data Validation for the Novel Approach

Although 2 alternative approaches are discussed in this study, it is worth noting that the conventional approach is considered fully transparent, whose mobility data was entirely based on publicly available statistics and clearly defined calculation assumptions, whereas the novel approach partly works like a black box, as both Telia Crowd Insight and Fyma are for-profit data services, whose mobility data was produced using undisclosed algorithms in terms of data processing and analysis even if their respective working principles can be explained in Fig. 1. In order to gain a deeper understanding of such mechanism, as a means of validation, we also calculated another set of commuting emissions result using stand-alone Telia Crowd Insight data produced using our own

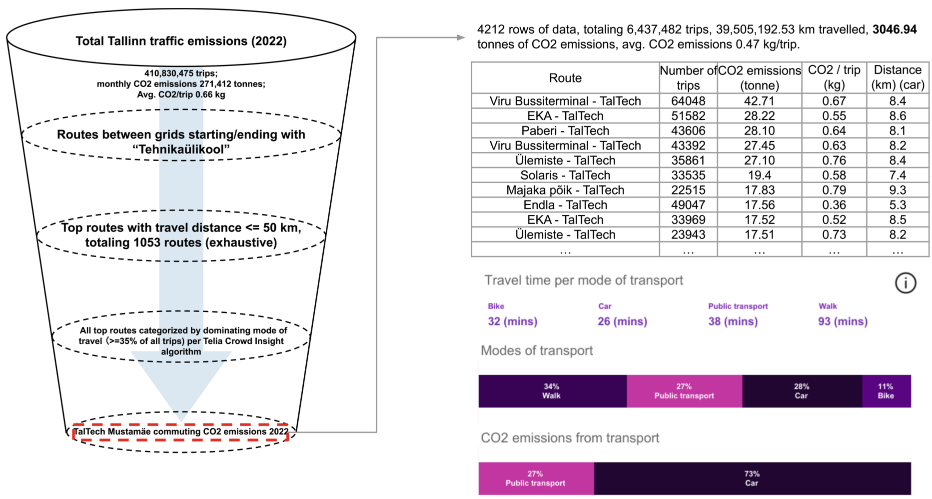

Fig. 4. Data screening process and its resulting travel emissions insight produced on stand-alone Telia Crowd Insight data

selection of filters (see Fig. 4) and normalized with a weighted average Fyma factor of 0.4 as opposed to a serie of month-specific Fyma factors used in the novel approach, and compared this result against that from the novel approach.

4.2 Error Interpretation

Table 3 below entails a side-by-side comparison of the 3 sets of results (the third set of result, i.e. the data validation result, consists of 2 values, one unnormalized, the other normalized) and the most probable crucial data contributing to the difference among them. As shown in Table 4, the difference observed between the commuting emissions obtained using the conventional approach and the novel approach was drastic, in which, the former value was 175% more than the latter, whereas the difference between the commuting emissions obtained using the novel approach and that from data validation (normalized) was comparatively moderate, in which, the former value was 18.5% more than the latter. Notably, the difference between the commuting emissions obtained using the conventional approach is 30.5% greater than the unnormalized data validation value, this significant yet uncontradictory difference suggests that the Fyma camera data is the decisive factor in differentiating the novel approach from the conventional one. Of all 3 sets of results, the drastic difference between the first two is contributed by the different fundamental assumptions taken. With the conventional approach, it considered the distribution of means of commuting in the city of Tallinn as a proper reflection of a similar pattern on the Mustamäe Campus, and calculated the accumulative travel distance/time of each means of commuting separately. With the novel approach, due to GDPR requirement, it could not distinguish specific commuting modes among what was algorithmically recognized as general public transport. The moderate difference between the latter two (the inventory value and the normalized data validation value) is contributed by the different data filters adopted for the same collected data, which means, the validation process approximated similar accumulative commuting activities as the novel approach did with its undisclosed algorithms. If the selection of data filters (as shown in Fig. 4) for the validation process continues to optimize, such difference is expected to be further reduced to a more tolerable range.

4.3 Suggested Application

Based on the case study on TalTech's Mustamäe Campus, for entities (communities, institutions, private corporates) looking to document their commuting emissions by adopting a similar approach discussed in this paper, it is advisable to use the conventional approach if the entity is located in a central location such as downtown and survey statistics on distribution of commuting modes already exists or is easy to obtain. For entities located outside of city center who are also not stringent with acquiring the emissions of any specific means of public transport, it is advisable to adopt an approach similar to the novel approach – if similar data services like Telia Crowd Insight and Fyma are available.

Table 3. Differences between the conventional approach, the novel approach, and the arithmetic validation of the novel approach

Approach	Practice	Data attribute	Critical metrics	Emissions, tCO_2
Conventional	the PICSOU framework	Publicly available data: fully based on existing survey statistics	Total annual travel distance (km): 22540034.3 by car; Total annual travel time (min): 44205608 by bus; 2675717 by tram; 6654773 by train	3975
Novel	TalTech 2022 GHG Inventory	Sampled and filtered Telia Crowd Insight data normalized by month-specific Fyma factors derived from camera footages	Total annual passenger-km: 11760009 by car; 4204780 by public transport	1444
	Data validation	Sampled and filtered Telia Crowd Insight data normalized by a single weighted average Fyma factor of 0.4 derived from camera footages	Total annual travel distance (km): 39505192.5 by all means of traveling including walking and biking	3046.9 (unnormalized) 1218.8 (normalized)

Table 4. Comparison of emission values measured using different methods, percentage difference calculated using the same equation: *[(bigger value – smaller value)/smaller value] * 100%*, only percentage differences relevant to the discussion were calculated.

	PICSOU 3975 t	Inventory (TCI + Fyma) 1444 t	Validation (unnormalized) 3046.9 t	Validation (normalized) 1218.8 t
PICSOU 3975 t	0%	175%	30.50%	-
Inventory (TCI + Fyma) 1444 t	-	0%	-	18.50%

5 Conclusions

This study holds several significant implications for sustainable transportation and corporate environmental management. By developing a comprehensive workflow for documenting corporate commuting emissions, organizations can gain a deeper understanding of their environmental impact and identify opportunities for emissions reduction. The university case study provides a practical example, demonstrating how alternative approaches to data collection and analysis can be employed to inform decision-making and foster sustainable commuting practices.

In conclusion, this study presents a comprehensive workflow for documenting corporate commuting emissions within a university context. By conducting a case study at TalTech's Mustamäe Campus and comparing two alternative approaches, we have shed light on effective strategies for understanding and managing commuting emissions. The findings demonstrate the significant impact of adopting different methodologies, with the conventional approach resulting in higher total annual commuting emissions of 3975 tons, while the novel approach yielded lower emissions of 1444 tons in 2022. These results emphasize the importance of selecting an appropriate approach based on the entity's location and data availability. The insights gained from this study contribute to the broader discourse on sustainable transportation strategies and provide practical recommendations for reducing corporate commuting emissions. By implementing similar approaches, organizations can take meaningful steps towards a greener and more environmentally conscious future.

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Publication III

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Quantitative Carbon Emission Prediction Model to Limit Embodied Carbon from Major Building Materials in Multi-Story Buildings

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Abstract: As the largest contributor of carbon emissions in China, the building sector currently relies mostly on enterprises' own efforts to report carbon emissions, which usually results in challenges related to information transparency and workload for regulatory bodies, who play an otherwise vital role in controlling the building sector's carbon footprint. In this study, we established a novel regulatory model known as QCEPM (Quantitative Carbon Emission Prediction Model) by conducting multiple linear regression analysis using the quantities of concrete, rebar, and masonry structures as independent variables and the embodied carbon emissions of a building as the dependent variable. We processed the data in the detailed quantity list of 20 multi-story frame structure buildings and fed them to the QCEPM for the solution. Comparison of the QCEPM-calculated results against the time-consuming and error-prone manual calculation results suggested a mean absolute percentage error (MAPE) of 2.36%. Using this simplified model, regulatory bodies can efficiently supervise the embodied carbon emissions in multi-story frame structures by setting up a carbon quota for a project in its approval stage, allowing the construction enterprise to carry out dynamic control over the three most important audited building materials throughout a project's planning and implementation phase.

Keywords: regulatory model; building LCA; embodied carbon emissions; low-carbon construction technology; environmental impact assessment

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1. Introduction

1.1. Global Warming: Consequences, Causes, and Challenges

In 2022, the carbon dioxide emissions (in terms of carbon dioxide equivalent) generated from energy use, industrial processes, flaring, and methane emissions amounted to 39.3 Gt, representing a 0.8% increase from the previous year, reaching an all-time high in history [1]. The warming caused by human greenhouse gas (GHG) emissions has resulted in anomalies in the climate system, including longer-lasting heatwave events globally [2], a continuous increase in the likelihood of droughts [3], significant increases in surface runoff and expansion of flood-affected areas [4,5], and a growing number of reports of extreme weather. This poses significant risks to ecosystems and human societies, such as altered water availability and threatened water security [6], causing irreversible harm to terrestrial, wetland, and marine ecosystems [7–9]; challenging human societies with climate anxiety; and reducing the healthcare system's ability to respond to climate-sensitive diseases [10]. Climate change has also severely impacted food/nutrition security and food production systems [11,12]. It is estimated that it is only possible to alter the global warming trend by containing the rise in the Earth's median surface temperature within 1.5 °C by the end of the 21st century, and, to achieve that, carbon neutrality has to be achieved by 2050 [13]. Over the past two decades, China's carbon emissions have seen a rapid increase and currently account for 32.1% of global carbon emissions, with 50.9% of the Chinese total national carbon emissions consisting of carbon emissions from the construction industry [14]. However, there has yet to be a reasonable and unified method for calculating carbon emissions in the Chinese construction industry, leading to difficulties in government regulation and undermotivated corporate participation, resulting in ineffective control over carbon emissions.

1.2. Common Practices for Analyzing Carbon Emissions

Through a literature review, we identified four categories of methods for calculating carbon emissions in terms of emission composition analysis, deciding factors affecting carbon emissions, and prediction of carbon emissions.

1.2.1. Input–Output Analysis

Input–output analysis (IOA) is a method that utilizes mathematical approaches to investigate the quantitative relationships between inputs and outputs in a given system [15]. It has been employed to study and analyze the interdependencies between various sectors of the national economy in terms of the production and consumption of products. This method involves creating input–output models to trace the sources of carbon inputs and the destinations of carbon outputs across different sectors of the national economy, as well as the inter-sectoral connections related to carbon-providing or carbon-consuming products. IOA can be combined with various other methods and applied at different scales. For example, the mathematical structure of IOA is closely related to LCA [16–18] and is an important tool for research and application in the field of sustainability [19–21]. Since IOA requires the collection of extensive data from various industries, and data collection methods and timing vary significantly between different industries, this can lead to inaccurate assessments of carbon emissions [22]. Therefore, IOA is suitable for macro-level research spanning multiple regions, sectors, or countries.

1.2.2. Decomposition Analysis

Decomposition analysis is a method that decomposes comprehensive statistical metrics into several relatively independent and simpler portions to study the nature of changes. It has been used to investigate the driving factors of carbon emissions [23–25]. Commonly employed analysis models include index decomposition analysis (IDA) [26] and structural decomposition analysis (SDA) [27]. This method is a form of comparative static analysis and is therefore less concerned with processes of change.

1.2.3. Econometrics

Econometrics is a method that uses mathematical and statistical approaches to determine specific quantitative relationships within economic contexts [28]. It has been applied to identify the impact factors of carbon emissions as well as each factor's respective extent of impact [29]. The Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework is widely used to examine the relationship between carbon emissions and impact factors [30]. It involves simulating different variables such as human behavior and economic activities to assess their impact on carbon emissions [31–34]. Econometrics is a complex computational process and may miss some key impact factors when identifying variables. Additionally, since the general form of econometrics is often a mathematical model with linear relationships between variables, issues like multicollinearity can arise, leading to significant errors in calculations [35].

1.2.4. Data Envelopment Analysis

Data envelopment analysis (DEA) is a quantitative analytical method that uses nonparametric programming to evaluate the relative efficiency of comparable units of the same type [36]. Common DEA models include CCR [37] and BCC [38]. This method is primarily used for assessing the efficiency of various decarbonization measures and providing optimization decisions or recommendations [39–41]. It is not used for carbon emissions calculations.

1.3. Problem Statement

The above methods all involve collecting adequate data and harnessing algorithmic approaches to tackle detailed and complex research inquiries, which would be impossible without having certain prerequisites in place. However, among China's 143,446 construction enterprises in 2022, companies capable of and willing to implement such prerequisites (usually falling under categories like state-owned enterprises, collective enterprises, and foreign-funded enterprises) account for only 4.66%, and they are responsible for only 13.4% of the country's total construction area [42]. More projects are completed by small- and medium-sized private enterprises with lower standardization and less capital investment. Therefore, the data collection and tracking mentioned in the above methods are not suitable for the current Chinese construction industry as the significant differences in the level of operation between each enterprise may result in considerable errors in the calculation results, making it difficult to formulate unified carbon emission management measures on the basis of these methods. The Chinese construction industry calls for a different carbon emissions measurement method, one that requires less additional investment and is relatively practical for all enterprises to implement.

From an auditing perspective, internationally recognized project-based carbon emissions accounting methods include real-time monitoring [43–45], mass balance [46,47], and emission factor [48,49]. The principles, characteristics, and application scenarios of these three methods are outlined in Table 1.

Table 1. Comparison of three carbon emissions accounting methods.

Method	Principles	Characteristics	Applicability
Real-time monitoring	Basic data measured from emissions sources are summarized into carbon emissions	High result accuracy, high data acquisition difficulty, high equipment investment	Narrow application scope, generally used for emissions in small regions with available monitoring data
Mass balance	Carbon emissions are obtained by subtracting the non-CO_2 carbon output from the input carbon content	Can describe GHG production in great detail only if the intermediate reaction processes are clear and demands high data accuracy and large workload	Can be used to check the accuracy of calculations by other methods, mainly used for accounting emissions during the production process
Emission factor	Carbon emissions are obtained by multiplying the volume of production or consumption activities that result in greenhouse gas emissions with the coefficient corresponding to the activity volume data	Simple and easy to understand, with a large number of reliable data and application cases. However, emission factors vary from region to region, leading to uncertainty when the emission system changes	Suitable for carbon emission calculations when the internal complexity of emission sources is low

For the regulatory bodies and the companies they regulate, real-time monitoring requires the deployment of monitoring equipment and dedicated personnel to track the carbon emissions throughout the construction process. The significant additional investment can lead to a lack of motivation for business participation, which is not conducive to regulation. The mass balance method focuses on the carbon dioxide production process and is more suitable for decarbonization research in the production of building materials. Although the Chinese construction industry currently adopts the emission factor method as the standard for carbon accounting, such a method requires considerable time and financial resources both in terms of tracking by enterprises and supervision by the government.

Therefore, the regulatory bodies are also in need of a regulatory tool that is flexible, time efficient, and effective.

According to the 2023 National Carbon Emission Trading Quota Allocation Regulations [50], the Chinese electricity industry adopts an annual measurement method to determine the carbon emissions of enterprises, making it the only sector in China that has established a carbon emission trading market based on a unified calculation method. However, we tend to presume that controlling a company's carbon emissions on an annual basis may not be reasonable in this context [51]. This is because the production cycle of building products is relatively long, and each construction company undertakes different types and quantities of projects in different years, leading to significant fluctuations in the calculation results. Additionally, the complexity of the sources of raw materials for construction projects and the production of products determines that the actual measurement method for carbon emissions cannot be widely applied.

Alternatively, controlling on a per-project basis can be more reasonable. Before project commencement, emission limits can be set according to a unified accounting standard. During construction, control is undertaken by the construction company against the emission limit benchmark. After project completion, regulatory bodies conduct reviews and establish a reward/penalty mechanism based on the review results. This approach facilitates the effective control of buildings' embodied carbon emissions.

1.4. Research Concepts: Scope, Objective and Novelty

From the perspective of building life cycle assessment (LCA), the carbon emissions from part of the Construction Process stage (module A4), Use stage (modules B1 through B7), and End of Life stage (modules C1 through C4) account for a high proportion (89.8% for buildings; considering central heating, building service life is typically 50 years) [52]. This part of carbon emissions is mainly caused by the consumption of electricity and fuel by transportation vehicles, construction facilities, indoor equipment, etc., which is relatively simple and can be obtained from electricity and gas management companies for calculating carbon emissions. Therefore, this part of carbon emissions is not within the scope of this study.

On the other hand, pre-operation carbon emissions (mostly occurring during modules A1, A2, and A3 of the Product stage and module A5 of the Construction Process stage) (see Figure 1), though accounting for a relatively lower percentage in a building's life cycle carbon emissions (10.2% for buildings; considering central heating, building service life is typically 50 years) [52], should not be overlooked, as China's annual new construction area has seen an increasing trend for over a decade. In 2022, the total floor space under construction exceeded 15,563,641,000 m^2 [42]. For the stated reasons, this part of the carbon emissions from modules A1, A2, A3, and A5 will be the focus and scope of this study.

The Ministry of Housing and Urban-Rural Development of the People's Republic of China has approved the use of the factor method for calculating the carbon emissions of each stage of building LCA [53], whose principle can be expressed using Equation (1):

$$C = \sum_{i=1}^{n} E_i F_i \quad (1)$$

in which C is the total emission and E_i is the amount of consumption by one of the contributing sources with F_i being its corresponding emission factor.

However, hundreds of emission factors can be found in specifications on the national, industrial, and local levels; therefore, carbon emission calculation requires a considerable volume of computing power, time, and financial input, which, in return, hinders the regulatory agencies' effort in establishing a nationwide regulation on building carbon emissions.

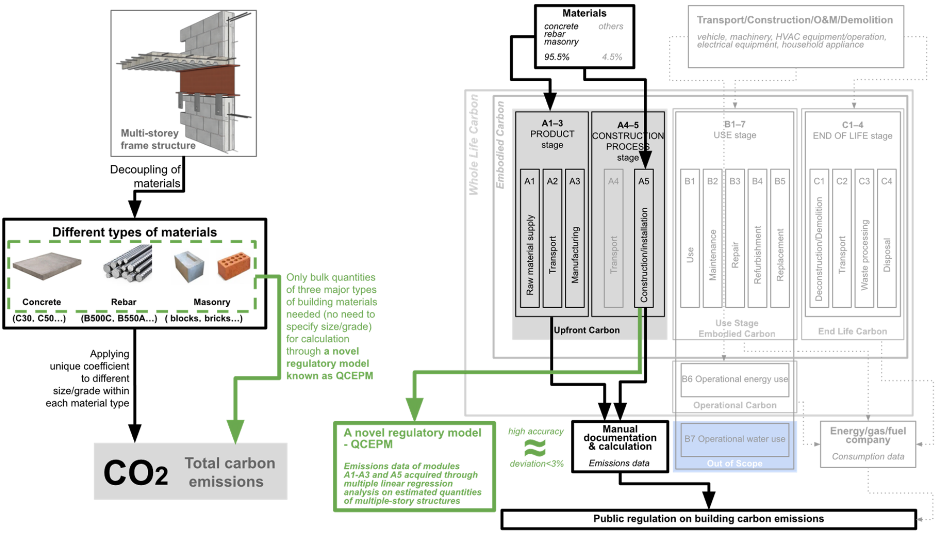

Figure 1. On the left: comparison between the conventional calculation method (text box and arrows denoted in black) and QCEPM (dotted box, text and arrow denoted in green) within the scope of a project's workflow; on the right: comparison between the conventional calculation method (text boxes and arrows denoted in black) and QCEPM (text box and arrow denoted in green) in terms of stages/modules covered within the scope of building LCA (text boxes and dotted arrows denoted in gray) according to ISO 21930: 2017.

Typically, the construction cost process in China involves investment estimation, design budget estimation, construction drawing budgeting, contract pricing, completion settlement, and final accounts on completion (all of which occur in module A5). Before the final accounts on completion, regulatory agencies are invited to conduct audits, which involve reviewing and evaluating the authenticity and legality of the entire cost of the construction project, as shown in Figure 2. If such readily available data can be utilized, the data acquisition and calculation for the carbon emissions of modules A1 through A5 (excluding A4) will be greatly simplified. Among these costs, the construction drawing budget is based on the construction drawings and includes the quantity of all building materials for the project, while the audit certifies all building materials used in the project after completion, which is the actual quantity of building materials recognized by all participating parties. Therefore, we can use the former to calculate the carbon emissions of the project as the emission limit and the latter as the actual carbon emissions at the end of the project, with their difference being the amount the project is over/under emission.

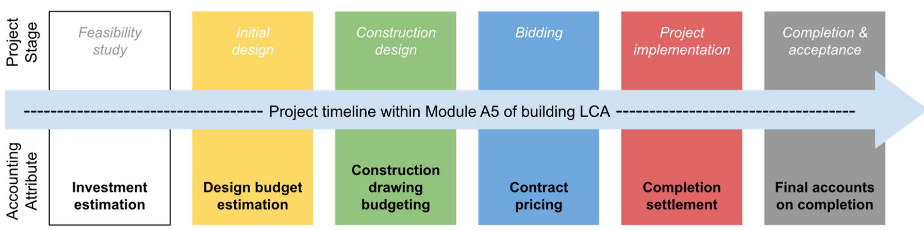

Figure 2. Project timeline within module A5 of building LCA.

However, the above-mentioned method still demands large computing power because the calculation lists in the design budget and project audit are based on structural components rather than building materials. If the factor method is to be used, it is necessary to screen out the same type of materials from thousands of items for summary and then multiply by the corresponding carbon emission factor to calculate the material's contribution to building carbon emissions (further elaboration for the factor method is given in the Method section). Therefore, the objective of our research is to study the internal relationship between material use and carbon emissions in order to identify a simplified regulatory model as part of a more comprehensive public regulation process, as illustrated in Figure 1.

The novelty of this study lies in its proposal of a novel regulatory model known as the Quantitative Carbon Emission Prediction Model (QCEPM), which does not require additional investment from construction companies and regulatory agencies or long-term tracking of the construction product production process. Instead, it uses existing data that are recognized by all parties involved in the workflow to calculate the carbon emissions of building projects of different scales. Regulatory bodies can then use the calculation results to develop quantifiable greenhouse gas emission management measures.

1.5. Article Structure

To ensure clarity and coherence, this paper is organized as follows: Section 1 provides a comprehensive review of the relevant literature, highlighting the current state of research and identifying gaps that this study aims to address. In Section 2, we describe the methodology used in this research, including how we obtain and process data. Section 3 presents the results of the study, discusses the reliability of QCEPM, and presents a case study. Finally, Section 4 concludes the paper by summarizing the key findings, acknowledging the limitations of the study, and suggesting directions for future research.

2. Method

2.1. Multiple Linear Regression Analysis

Multiple linear regression (MLR) is a statistical technique that models the relationship between more than two independent variables and a dependent variable by fitting a linear equation to observed data. It has been widely used in environmental and engineering issues [54–56] thanks to its robustness in predicting outcomes. Since MLR provides a clear linear relationship between the dependent variable and the independent variables, and the coefficients in the MLR model are easy to interpret, we believe that the clarity of the methodology facilitates sustainability assessment and policy formulation, which are exactly the expected outcomes of this paper.

2.1.1. Selection of Influencing Factors

Since we can obtain material usage from the quantity list from the stages mentioned in Figure 2 and MLR is well suited to utilize this type of data, the selection of the influencing factor is the key to building QCEPM. Within the scope of this paper, the main building materials that make up the emissions are shown in Table 2.

There have been adequate research studies aimed at analyzing the composition of a building's embodied carbon emissions, which show that concrete, rebar, and masonry combined contribute more than 80% of embodied carbon emissions, particularly in frame structures, where the share reaches up to 95.5% [57–62]. Hence, we considered the contribution of other building materials (such as plastics, tiles, timber, stone, etc.) to QCEPM as negligible, based on which we also set the boundaries for data processing.

Therefore, the quantity of concrete, rebar, and masonry are regarded as the influencing factors in this study, which are used for calculating the embodied carbon emissions of frame structure buildings.

Table 2. Major building materials and their emission source.

No	Building Material	Emission Source
1	Plastics (polyvinyl chloride, polyurethane, polypropylene, polycarbonate, ABS, and nylon)	Petrochemical extraction and processing, energy-intensive production
2	Tiles	High-temperature firing during manufacturing, transportation
3	Clay	Energy use in extraction and processing
4	Gypsum	Energy use in extraction and processing
5	Stone (granite, marble, sandstone, and slate)	Energy use in extraction and transportation
6	Metal (aluminum, stainless steel, copper, and titanium)	Energy-intensive extraction and processing
7	Timber	Deforestation, transportation, processing
8	Masonry	Energy-intensive firing, transportation
9	Gravel	Energy use in extraction and transportation
10	Sand	Energy use in extraction and transportation
11	Rebar (including steel)	Energy-intensive steel production process
12	Concrete (including mortar)	Cement production, energy-intensive manufacturing process

2.1.2. Modeling and Solving

In this section, we describe the process of modeling and solving multiple linear regression analysis, whose general equation can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_i x_m + \varepsilon \tag{2}$$

where ε is the random error caused by either subjective or objective reasons, which follows a normal distribution of $\varepsilon \sim N(0, \sigma^2)$; $\beta_0,\ \beta_1,\ \cdots,\ \beta_i$ are the regression coefficients; and $\beta_0,\ \beta_1,\ \cdots,\ \beta_{\mathrm{i}}, \sigma^2$ are all unknown parameters that need to be solved. y represents the dependent variable, while $x_1,\ x_2,\ \cdots,\ x_m$ represent a set of m independent variables that are both measurable and controllable.

By letting $(x_{i1}, x_{i2}, \cdots, x_{im})$, I = 1, 2, …, n be the n observed values of $(x_1, x_2, \cdots, x_m)$, we had the following:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_2 x_{i3} + \cdots + \beta_m x_{im} + \varepsilon_i \tag{3}$$

in which i = 1, 2,…, n, each of the ε_i is independent, and $\varepsilon_i \sim N(0, \sigma^2)$.

Then, the unbiased estimate of $\hat{\sigma}^2$ can be expressed as follows:

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{m} x_{ij} \hat{\beta}_j \right)^2}{n - m - 1} \tag{4}$$

We then obtained the following formulae:

$$\beta = (\beta_0,\ \beta_1,\ \cdots,\ \beta_m)^T, \varepsilon = (\varepsilon_0,\ \varepsilon_1,\ \cdots,\ \varepsilon_m)^T, Y = (y_0,\ y_1,\ \cdots,\ y_m)^T \tag{5}$$

$$X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1m} \\ 1 & x_{21} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{6}$$

Under the assumption that the errors are normally distributed with a mean of zero, ε is typically ignored because this term does not bias the estimates of the regression coefficients. The equation set can be expressed in matrix form as follows:

$$Y = X\beta \tag{7}$$

Assuming that the rank of the matrix is $m + 1$, i.e., full column rank, we solved for $X^T Y = \left(X^T X\right)\hat{\beta}$, and obtained $\hat{\beta} = \left(X^T X\right)^{-1} X^T Y$.

In this study, we considered the carbon emissions as the dependent variable E, the quantity of concrete as independent variable C, the quantity of rebar as independent variable R, and the quantity of masonry as independent variable M. After introducing abundant sets of concrete, rebar, and masonry data for solving β_i (i = 0, 1, 2, 3) and ε, the model can be expressed as follows:

$$E = \beta_0 + \beta_1 C + \beta_2 R + \beta_3 M \tag{8}$$

2.2. Data Source and Processing

2.2.1. Collection of Raw Data

To ensure consistency between research data and actual construction, we decided to use detailed schedules of quantities that have been audited and approved by all participating parties upon project completion. These schedules list the quantities of all construction entities in the project along with their corresponding material usage and prices. However, we encountered difficulties during data collection as companies were generally reluctant to disclose these schedules due to concerns over data security, which added significant challenges to our work. Eventually, with the help of several cost consulting firms, we removed incomplete data from the acquired information, resulting in the selection of 20 sets of data from buildings in Sichuan Province, most of which are located in the metropolis of Chengdu. All of these buildings, built between 2015 and 2023, are no more than 24 m in height, with number of floors ranging from 3 to 7 and gross building area from 2000 to 10,000 m^2 (see Table 3).

Table 3. Distribution of selected data.

Dataset #	Building Classification	City	Structure Type	No. of Floors	Gross Building Area (m^2)	Year
1	School	Chengdu	Framing	5	2411.92	2015
2	School	Chengdu	Framing	5	3054.08	2018
3	School	Chengdu	Framing	4	4640.73	2020
4	Multi-Family Home	Chengdu	Framing	5	4940.44	2017
5	Multi-Family Home	Chengdu	Framing	5	4964.08	2018
6	Multi-Family Home	Chengdu	Framing	5	5277.91	2020
7	Apartment Building	Chengdu	Framing	6	5387.06	2023
8	Apartment Building	Chengdu	Shear wall framing	7	5594.79	2023
9	Apartment Building	Chengdu	Framing	4	5775.11	2019
10	Apartment Building	Chengdu	Framing	3	5786.97	2022
11	Apartment Building	Chengdu	Framing	5	6075.29	2022
12	Hospital	Bazhong	Shear wall framing	4	6869.34	2019
13	Office Building	Luzhou	Shear wall framing	6	6995.58	2018
14	Apartment Building	Chengdu	Framing	7	7575.78	2016
15	Hotel/Motel	Chengdu	Framing	5	7960.50	2021
16	College	Chengdu	Framing	5	8029.49	2019
17	School	Chengdu	Framing	5	8051.75	2021
18	Retail and Service	Chengdu	Framing	6	8876.40	2019
19	Retail and Service	Chengdu	Framing	6	9009.63	2023
20	Recreational Facility	Chengdu	Framing	6	9934.70	2023

2.2.2. Data Processing

Take dataset #16 of Table 3, a school building (as shown in Figure 3) with a gross building area of 8029.49 m^2, as an example.

Figure 3. Reference building.

The main building components are shown in Figure 4. In the detailed quantity list, the quantities and prices of building materials are categorized and summarized according to different types of building components (such as beams, walls, stairs, etc.). This list comprises a total of 8 pages, and Table 4 showcases the second page of this dataset in the detailed quantity list.

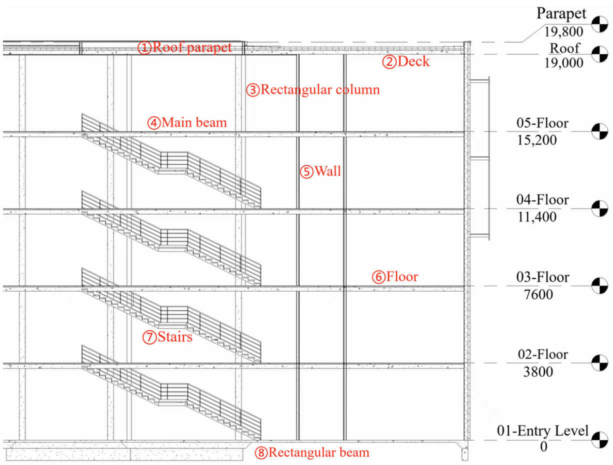

Figure 4. Structural model of the reference building.

For data processing, we first filtered out information such as codes, prices, and project characteristics from the detailed quantity list, retaining only the components and their corresponding quantity information. Then, we sorted the detailed quantity list by material types instead of the default component types and recalculated the quantity of each material. Finally, based on the carbon emission factors provided by the Chinese Emission Accounting Database System (CEADS), we calculated the carbon emissions of each material and aggregated the total carbon emissions of concrete, rebar, and masonry, whose processed data results are shown in Table 5. We also applied the same workflow for processing other datasets.

Table 4. Page 1 in the detailed quantity list of dataset #16.

No.	Item Code	Item Name	Item Features	Unit	Quantity	Cost (CNY)		
						Unit Price	Subtotal	Labor Cost
10	010401003001	Solid brick wall	1. Block type: aerated concrete block 2. Wall type: interior wall 3. Mortar strength grade: M5 4. Wall thickness: 120 mm	m^3	12.36	322.24	3982.89	1198.12
			Masonry project cost subtotal				461,858.24	143,531.11
			Concrete and Reinforcement Works					
11	010501001001	Bedding	1. Concrete type: commercial concrete 2. Concrete strength grade: C15	m^3	85.72	362.3	31,056.36	1911.98
12	010501002001	Strip foundation	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	21.45	402.65	8636.84	500.32
13	010501003001	Independent foundation	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	347.86	402.65	140,065.83	8113.83
14	010502001001	Rectangular column	1. Concrete type: commercial concrete 2. Concrete strength grade: C25	m^3	184.17	389.87	71,802.36	5027.84
15	010502001002	Rectangular column	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	139.67	409.97	57,260.51	3812.99
16	010502002001	Structural column	1. Concrete type: commercial concrete 2. Concrete Strength Grade: C25	m^3	71.01	389.87	27,684.67	1938.57
17	010502002002	Structural column	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	16.02	409.97	6567.72	437.35
18	010503002001	Rectangular beam	1. Concrete type: commercial concrete 2. Concrete strength grade: C25	m^3	75.44	389.37	29,374.07	2013.12
19	010503002002	Rectangular beam	1. Concrete type: commercial concrete 2. Concrete strength grade: C30	m^3	13.5	409.47	5527.85	360.25
			Subtotal for this page				377,976.21	24,116.25

Table 5. Processed results from dataset #16.

No.	Material Name	Unit	Quantity	Carbon Emission Factor ($kgCO_2e$/unit)	Carbon Emissions ($kgCO_2e$)
1	Concrete (C15)	m^3	85.72	228	19,544
2	Concrete (C20)	m^3	1772.20	263	466,089
3	Concrete (C30)	m^3	912.39	248	226,273
4	Gravel concrete	m^3	217.86	295	64,269
	Concrete project subtotal		2988.17	—	776,175
5	Rebar (HPB300)	t	41.21	2310	95,188
6	Rebar (HRB335)	t	6.09	2340	14,248
7	Rebar (HRB400)	t	216.50	2350	508,784
	Rebar project subtotal		263.80	—	618,220
8	Solid brick	m^3	60.17	341	20,518
9	Porous brick	m^3	445.95	341	152,069
10	Building blocks	m^3	885.68	327	289,617
	Masonry project subtotal		1391.80	—	462,204
	Grand total		—	—	1,856,599

3. Results and Discussion

3.1. Results of Multiple Linear Regression Analysis

We applied the data processing method described in Section 2.1.2 to all 20 sets of data. This yielded the total quantities of concrete, rebar, and masonry used in each project. We then converted the quantities into carbon emissions, added up the total carbon emissions for each dataset, and calculated their respective carbon emissions per unit area; the results are listed in Table 6.

Table 6. Process carbon emissions data (in ascending order of gross building area).

Dataset #	Quantity			Carbon Emissions ($kgCO_2e$)	Gross Building AREA (m^2)	Carbon Emissions/Unit Area ($kgCO_2e/m^2$)
	Concrete (m^3)	Rebar (t)	Masonry (m^3)			
1	1618.60	138.43	597.43	971,114	2411.92	403
2	1259.19	168.43	643.17	977,463	3054.08	320
3	2028.72	228.79	3925.88	2,436,650	4640.73	525
4	3797.81	187.73	918.32	1,737,206	4940.44	352
5	1897.44	168.73	1006.18	1,289,469	4964.08	260
6	2089.77	158.16	1285.66	1,359,165	5277.91	258
7	609.90	260.84	1172.56	1,181,111	5387.06	219
8	2192.10	214.19	780.68	1,405,111	5594.79	251
9	1715.64	211.94	1545.25	1,442,745	5775.11	250
10	2291.90	256.95	1384.37	1,862,171	5787.97	322
11	3026.36	294.37	1420.99	2,053,805	6075.29	338
12	3417.75	236.94	1790.69	2,189,108	6869.34	319
13	2756.31	230.94	1672.39	1,923,117	6995.58	275
14	3479.03	580.38	2020.19	3,078,583	7575.78	406
15	2560.02	295.90	1248.16	1,768,854	7960.50	222
16	2988.17	263.80	1391.80	1,856,599	8029.49	231
17	2735.34	412.73	1259.19	2,194,157	8051.75	273
18	2459.30	340.31	2161.22	2,249,876	8876.40	253
19	3266.15	447.05	1740.60	2,604,958	9009.63	289
20	3942.87	607.96	1123.67	2,909,373	9934.70	293

All values in Table 6 were obtained through manual tasks, including raw data processing, calculating carbon emissions for different building materials, and computing the total carbon emissions of buildings. This manual calculation approach demands substantial labor and repeated verification, leading to significant manpower costs, all of which have rendered it unsuitable for effective regulation.

Alternatively, we input the quantities of concrete, rebar, and masonry from the aforementioned 20 datasets into the multiple linear regression process in Section 2.1 for a solution and obtained the expression of QCEPM as follows:

$$E = 271.499C + 2470.192R + 348.319M \quad (9)$$

where E represents the carbon emissions, C represents the quantity of concrete, R represents the quantity of rebar, and M represents the quantity of masonry. The constant β_0 is omitted from this equation; see Section 3.2.2 for a detailed discussion.

3.2. Discussion

We utilized SPSS Statistics 27.0.1 software to verify the statistical significance of the study, discussed the error of the model, and conducted a case study.

3.2.1. Verification of Multicollinearity

We evaluated the collinearity of the three independent variables, concrete, masonry, and rebar, by assessing their respective variance inflation factor (VIF) values. The interpretation of VIF values is as follows:

(1) When $0 < \text{VIF} \leq 5$, there is no multicollinearity;
(2) When $5 < \text{VIF} \leq 10$, there is a weak multicollinearity;
(3) When $10 < \text{VIF} \leq 100$, there is moderate to strong multicollinearity;
(4) When $\text{VIF} > 100$, there is severe multicollinearity.

The analysis results are shown in Table 7, indicating that the VIF values for the three independent variables are all less than 10. This suggests that there is no precise or high correlation among the three independent variables. Therefore, constructing a model using these three independent variables should not lead to estimation bias or undermine estimation accuracy.

Table 7. Collinearity analysis results.

	Collinearity Statistics	
	Capacity	**VIF**
Concrete	0.657	1.522
Rebar	0.642	1.557
Masonry	0.963	1.039

3.2.2. Model Validation

We first conducted an analysis of variance (ANOVA), and the results are shown in Table 8. The model's F-value is 666.835, indicating a high homogeneity of variance in the research data. The corresponding significance is 0, which is much less than 0.05. This suggests that the model parameters are statistically significant for the accurate estimation of carbon emissions.

Table 8. Analysis of variance results.

	Sum of Squares	Degrees of Freedom	Mean Square	F-Value	Significance
Between	6,842,727,600,158.907	3	2,280,909,200,052.969	666.835	0.000
Within	54,728,000,956.385	16	3,420,500,059.774	—	—
Total	6,897,455,601,115.293	19	—	—	—

Due to the small sample size of our research, we analyzed the significance of the three independent variables in the model. If the significance test result is greater than 0.05, the independent variable is statistically insignificant and should be removed from the model. Conversely, if the value is less than 0.05, the variable is statistically significant in the model and should be retained. The analysis results (see Table 9) from concrete (β_1 = 271.499, σ = 19.154, $p < 0.001$), rebar (β_2 = 2470.192, σ = 0.542, $p < 0.001$), and masonry (β_3 = 348.319, σ = 0.416, $p < 0.001$) suggest that these three independent variables can significantly explain the carbon emissions. Additionally, since the significance of the constant (β_0 = −18,040.215, σ = 7026.180, p =0.706) is greater than 0.05, it is not statistically significant in this model and should be omitted.

Table 9. Regression and *t*-test.

	Unstandardized Coefficients		Standardized Coefficients Beta	t	Significance
	B	Standard Error (σ)			
(Constant)	−18,040.215	7026.180	—	−0.384	0.706
Concrete	271.499	19.154	0.389	14.175	<0.001
Rebar	2470.192	126.637	0.542	19.506	<0.001
Masonry	348.319	19.021	0.416	18.312	<0.001

Since the value of adjusted R squared is not affected by the number of independent variables, we used this value as the criterion for deciding the model's goodness of regression fit, whose result is represented by an R^2 value of 0.991, as shown in Table 10. This suggests that using the quantities of concrete, rebar, and masonry for calculating the embodied carbon emissions in multi-story buildings achieved an explanation power of 99.1%, indicating a high degree of linear fit in the model. Additionally, the Durbin–Watson coefficient is close to 2.0, which shows that the autocorrelation between independent variables is vague, further denoting a high level of truthfulness of QCEPM.

Table 10. Model fit degree and Durbin–Watson test.

Model	R	R^2	Adjusted R Squared	Std. Error of the Estimate	Durbin–Watson
1	0.996	0.992	0.991	58,485.04133	1.939

3.2.3. Error Analysis

We utilized QCEPM to calculate the carbon emissions using 20 sets of data and compared them with the manually calculated carbon emissions from the same datasets listed in Table 6. The comparison yielded a relative error (RE) within ±6.6%, as listed in Table 11 and plotted in Figure 5. The RE calculation formula is as follows.

$$\mathrm{RE} = \frac{\hat{y}_i - y_i}{y_i} \tag{10}$$

in which $\hat{y}_i$ (i = 1, 2,. . ., n) represents the QCEPM calculation value and y_i (i = 1, 2,. . ., n) the manual calculation value.

The correlation between QCEPM—calculated results and manually calculated results is shown in Figure 6. The tight clustering of points along the fit line and the narrow confidence band suggest that this is a highly reliable model for calculating buildings' embodied CO_2e values based on given quantities of the three most important construction materials.

Additionally, we calculated the mean absolute percentage error (MAPE) of QCEPM using Equation (10) and the symmetric mean absolute percentage error (sMAPE) using Equation (11):

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{11}$$

$$\mathrm{sMAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{\frac{(|y_i|+|\hat{y}_i|)}{2}} \tag{12}$$

in which $\hat{y} = \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n\}$ represents the QCEPM calculation value and $y = \{y_1, y_2, \ldots, y_n\}$ the manual calculation value.

Table 11. Error analysis between QCEPM calculation and manual calculation.

Dataset #	Manual Calculation ($kgCO_2e$)	QCEPM Calculation ($kgCO_2e$)	RE (%)
1	971,114	989,493	1.9
2	977,463	981,952	0.5
3	2,436,650	2,483,409	1.9
4	1,737,206	1,814,699	4.5
5	1,289,469	1,282,420	−0.5
6	1,359,165	1,405,876	3.4
7	1,181,111	1,218,337	3.2
8	1,405,111	1,396,169	−0.6
9	1,442,745	1,527,567	5.9
10	1,862,171	1,739,167	−6.6
11	2,053,805	2,043,762	−0.5
12	2,189,108	2,136,934	−2.4
13	1,923,117	1,901,327	−1.1
14	3,078,583	3,081,874	0.1
15	1,768,854	1,860,731	5.2
16	1,856,599	1,947,712	4.9
17	2,194,157	2,200,764	0.3
18	2,249,876	2,261,123	0.5
19	2,604,958	2,597,340	−0.3
20	2,909,373	2,963,658	1.9

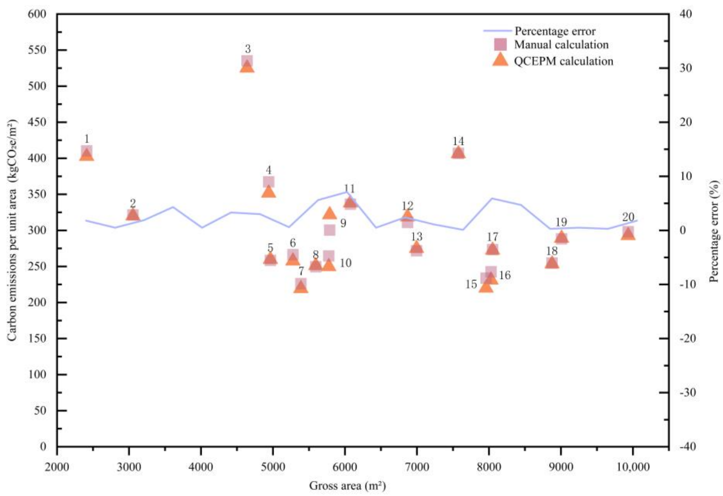

Figure 5. Distribution of 20 datasets in terms of specific carbon emissions ($kgCO_2e/m^2$) and the percentage error (%) between their QCEPM—calculated and manually calculated results.

The calculation obtained a MAPE value of 2.36%, indicating that QCEPM, which was identified in this study, achieved an accuracy of 97.64%. To achieve symmetrical treatment of under-forecasting and over-forecasting and ensure a balanced assessment of forecast error, we employed SMAPE as a complementary measure to MAPE. The sMAPE of QCEPM is 2.29%, which also suggests a high accuracy of this model.

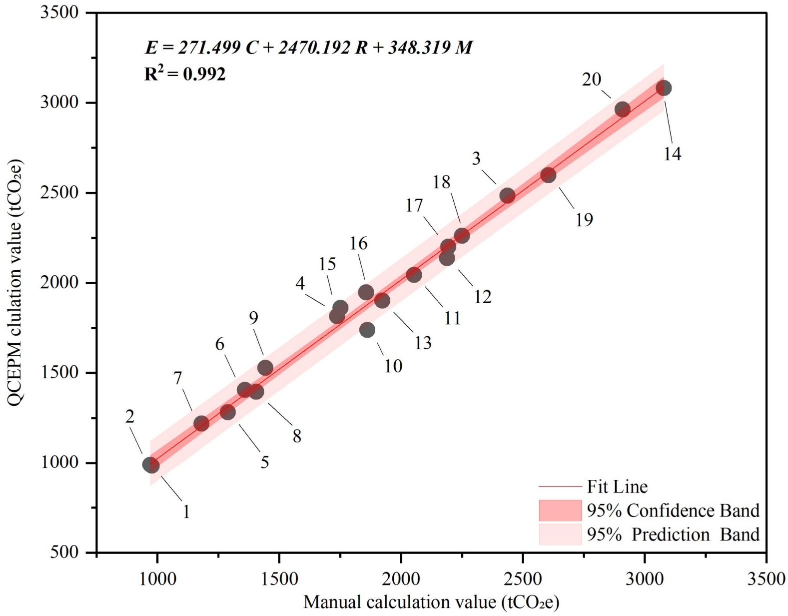

Figure 6. Correlation between QCEPM-calculated and manually calculated CO_2e values of 20 data sets.

3.2.4. Case Study

Through the above discussion, we concluded that the dependent variable can be well explained by the independent variables, and there is a very strong correlation between them, we were hence convinced that the 20 sets of data used for the solution are adequate for verifying this study. In order to further validate the feasibility of using QCEPM for calculating embodied carbon emissions, we analyzed 10 additional projects that are either under construction or have been completed (see Table 12).

Table 12. Case project information.

Dataset #	Project Name	City	Structure Type	Gross Building Area (m^2)	No. of Floors	Year
1	Jinjiang Commercial Building	Chengdu	Framing	1861.31	2	2023
2	Longjianglu Elementary School Building	Chengdu	Framing	3002.10	6	2023
3	Jinxiu Residence	Chengdu	Framing	4940.44	6	2023
4	Banan Middle School Building	Chongqing	Framing	5277.91	5	2023
5	Liangchen Residence	Chengdu	Framing	5648.51	3	2022
6	Zuoyu Residence	Chengdu	Framing	8315.25	6	2023
7	Rilian Residence	Chengdu	Framing	8798.40	6	2023
8	Xiayu Residence	Chengdu	Framing	10,264.80	7	2023
9	Aochuang Commercial Complex	Chengdu	Shear wall framing	13,645.65	5	2022
10	Tianchen Office Tower	Chengdu	Framing	18,109.90	6	2023

We collected data from the detailed quantity list of these projects, which correspond to different accounting stages shown in Figure 2. With the data, we then obtained each project's embodied carbon emissions using both manual calculation and QCEPM calculation and conducted error analysis. The results are shown in Table 13. The unit area error calculation formula is as follows.

$$E_A = \frac{\hat{y}_i - y_i}{A_i} \tag{13}$$

in which $\hat{y}_i$ (i = 1, 2,. . ., n) represents the QCEPM calculation value, y_i (i = 1, 2,. . ., n) represents the manual calculation value, and A_i (i = 1, 2,. . ., n) represents the gross building area of each project.

Table 13. Case study results (in ascending order of project gross building area).

Dataset #	Quantity			Manual Calculation ($kgCO_2e$)	QCEPM Calculation ($kgCO_2e$)	RE (%)	Unit Area Error ($kgCO_2e/m^2$)
	Concrete (m^3)	Rebar (t)	Masonry (m^3)				
1	716.42	98.11	600.42	642,724	645,996	0.5	1.8
2	1421.71	156.53	1106.59	1,149,603	1,158,098	0.7	2.8
3	2756.98	160.13	1104.71	1,526,346	1,528,861	0.2	0.5
4	1408.81	177.65	1121.72	1,186,996	1,212,037	2.1	4.7
5	2233.84	261.11	1097.11	1,622,969	1,633,621	0.7	1.9
6	2657.55	268.99	2318.96	2,206,884	2,193,717	−0.6	−1.6
7	3291.52	353.76	2425.03	2,634,964	2,612,184	−0.9	−2.6
8	2708.1	386.91	2739.7	2,649,052	2,645,278	−0.1	−0.4
9	4518.09	769.52	1405.15	3,610,614	3,616,960	0.2	0.5
10	4565.1	665.99	3741.03	4,183,085	4,187,615	0.1	0.3

The calculation results demonstrate a maximum RE no greater than 2.1% for the 10 sets of case study data, and the accumulative unit area error is 7.9 $kgCO_2e/m^2$ (see Figure 7. Such error is equivalent to the carbon emissions generated by the construction activities of an 18-story residential building in 4 days [63]. In summary, this study has achieved the goal of identifying a novel model known as QCEPM that utilizes existing data during the project process for fast calculation of embodied carbon emissions. By adopting a project-by-project supervision method, the error of this model has been reduced to an acceptable range both on the project and the accumulative level.

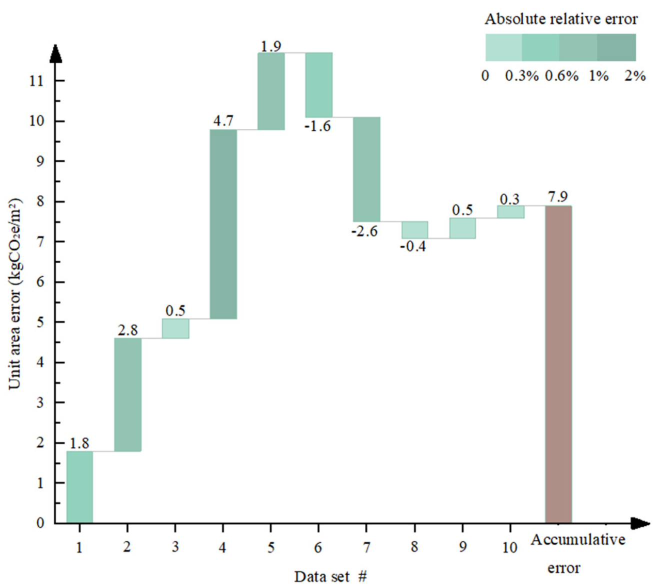

Figure 7. Accumulative unit area error of 10 case study projects.

4. Conclusions

4.1. Findings

This study has developed QCEPM, a novel regulatory model for estimating carbon emissions in the A1–A5 (excluding A4) stages of LCA for multi-story building structures using the quantities of concrete, rebar, and masonry. The significance of QCEPM lies in its innovative approach, utilizing readily available quantity data from multiple accounting stages such as construction drawing budgeting, contract pricing, completion settlement, and final accounts on completion. This allows for immediate and accurate estimation of carbon emissions, making it a valuable tool for regulatory bodies and the construction industry. QCEPM simplifies the daily monitoring and data collection of carbon emissions during project implementation. By enabling regular on-site reporting of quantity data, QCEPM provides dynamic control over carbon emissions, addressing the challenges of substantial workload, long work cycles, and high investment, all of which are traditionally associated with carbon monitoring processes in the building sector. QCEPM stands out as it not only complements existing methods for energy consumption calculation and carbon emissions monitoring and auditing but also offers a practical and efficient solution for regulatory bodies to obtain carbon emissions data of construction projects across different regions. By using a combination of historical emissions data and carbon peaking targets, QCEPM enables the development of future regulatory schemes tailored to each region, promoting the enhancement of the carbon emissions regulatory system in the construction industry and contributing to the effective control of GHG emissions and accurate assessment of emission reductions.

Moreover, QCEPM facilitates the establishment of a standardized building carbon trading market. In the early stages of a project, regulatory bodies can use QCEPM to quickly estimate the carbon emissions of the structure based on quantities from contract pricing, setting an upper limit for carbon emissions. Upon project completion, actual carbon emissions can be calculated using quantities from final accounts. If emissions exceed the upper limit, the project developer must purchase carbon credits from the carbon trading market. Conversely, if emissions are lower than the upper limit, the surplus credits can be sold in the carbon trading market. This process incentivizes project participants to actively manage and reduce carbon emissions, unleashing the potential of the building carbon trading market.

4.2. Limitations and Suggested Future Studies

Due to the extensive data processing involved in studying the complex relationship between different structural components with varying material compositions and their carbon emissions, we strived to define clear research boundaries. As a result, QCEPM is currently applicable to the calculation of embodied carbon emissions in multi-story buildings only. Additionally, the study was limited to the A1–A5 (excluding A4) stages of the life cycle assessment (LCA), and the applicability to other building types and stages was not explored in depth.

Our future research will aim to expand the scope of QCEPM to include high-rise buildings and additional LCA stages to provide a more comprehensive carbon emissions estimation. It is also essential to verify the reliability and robustness of QCEPM by incorporating other machine learning algorithms to enhance the accuracy of the model. Furthermore, given the favorable prediction results of the model, it is imperative to rigorously assess whether the model is subject to overfitting. One effective method is to perform k-fold cross-validation. This involves splitting the dataset into k subsets, training the model on $k-1$ subsets, and validating it on the remaining subset.

Furthermore, we are utilizing QCEPM to develop platform software, establishing a carbon emissions management platform for collaborative efforts between regulatory bodies and enterprises. This software will feature functions such as data collection, real-time calculation of building carbon emissions, analysis of carbon emission trends, and formulation of carbon trading strategies. Consequently, enterprises can upload planned construction quantity data in the pre-project phase, and the platform will automatically calculate emission limits. Upon project completion, enterprises can upload actual construction quantity data, and the platform will automatically calculate actual emissions and tradable carbon credits, integrating the data into the building carbon emissions trading market. With the carbon emissions management platform, regulatory bodies can gain better insights into the carbon emissions of the construction market, enabling them to formulate more scientific and practical carbon trading and emissions management policies. Enterprises, on the other hand, can adjust their development strategies based on market demand and policy guidance, thereby achieving their carbon reduction goals.

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Data Availability Statement: The datasets used for producing analytical results presented in this article are not readily available because the raw data of the projects discussed in this study are classified as trade secrets of companies providing the data, who demanded the data to be used and used solely by the persons directly involved in this study for the purpose of scientific research only. The authors had, prior to the commencement of this study, agreed to comply with the legally binding confidentiality rules set by the data providers and are therefore not obliged to redirect requests to access the datasets to any individual or entity.

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Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Chapter 2
Modularizing the PICSOU Framework: Subtropical Climate Adaptation and Validation of University Campus IEQ Benchmarking

Qidi Jiang, Cheng Liu, Chunjian Wang, Zhiyang Chen, Heidi Salonen, and Jarek Kurnitski

Abstract The PICSOU (Performance Indicators for Core Sustainability Objectives of Universities) framework, originally designed for temperate-climate university campuses, has demonstrated promise in sustainability assessment but lacks validation across diverse environmental contexts. This study advances PICSOU's theoretical foundation by modularizing its structure, enabling climate-specific adaptations that enhance its universality for global scalability. Focusing on Indoor Environmental Quality (IEQ) metrics, we apply the framework to Jincheng College, a large campus in Chengdu, China, situated in a subtropical monsoon climate characterized by high humidity and seasonal temperature fluctuations. For the case study, we deployed a network of high-resolution sensors across 6 dormitories, 4 classrooms, 2 offices, and 1 outdoor control site, collecting synchronized, real-time data (at 1-min intervals) over a 15-day monitoring period. Parameters included CO_2 levels, $PM_{2.5}$ concentrations, temperature, relative humidity, and occupancy patterns, providing a comprehensive dataset for analyzing human–environment interactions without reliance on assumptions. Our findings reveal significant deviations from

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temperate-climate benchmarks, particularly in CO_2 levels and thermal comfort, highlighting the need for climate-specific adaptations within PICSOU. By introducing modular components (e.g., localized thresholds, climate-adjusted ventilation strategies), we transform PICSOU into a scalable framework capable of addressing larger campuses and diverse climatic conditions. This work not only validates PICSOU's cross-climate applicability but also strengthens its theoretical foundation, positioning it as a universal tool for university sustainability benchmarking.

Keywords The PICSOU framework · Indoor Environmental Quality (IEQ) · University campus · Real-time occupancy detection · Climate-specific adaptations

2.1 Introduction

2.1.1 Campus Sustainability and the PICSOU Framework

University campuses play a critical role in advancing sustainability, balancing environmental, social, and economic objectives. As institutions with high energy consumption and significant environmental footprints, campuses are ideal settings for implementing innovative sustainability frameworks. The PICSOU (Performance Indicators for Core Sustainability Objectives of Universities) framework (Jiang and Kurnitski 2023) was proposed as a robust and comprehensive methodology for measuring campus sustainability across six key categories: space efficiency and learning environment, indoor environmental quality, climate change and energy, transportation, water, waste and consumables. Its modular architecture enables flexibility and scalability, allowing it to adapt to diverse campus environments and sustainability goals. This study focuses on the Indoor Environmental Quality (IEQ) category of the PICSOU framework, extending its universality to address diverse climatic and occupancy contexts, using Jincheng College in Chengdu, China, as a case study.

2.1.2 Gaps in Existing IEQ Benchmarking

While PICSOU introduced a modular methodology for campus sustainability assessment, its initial validation of the IEQ category was limited to temperate climate. This study addresses a critical gap by expanding PICSOU's applicability to subtropical monsoon climate, where high humidity and seasonal temperature fluctuations pose distinct challenges. For instance, in subtropical regions, high humidity and temperature variability can lead to suboptimal ventilation strategies and energy inefficiencies. Furthermore, prior studies (Xu et al. 2022; Chojer et al. 2020; Wang et al. 2023) have largely overlooked the dynamic interplay between real-time occupancy and IEQ fluctuations, relying instead on static models that inadequately capture real-world scenarios. These gaps highlight the need for a more adaptive and scalable approach to IEQ benchmarking, particularly on university campuses with diverse occupancy patterns.

2.1.3 Study Objectives

This study aims to address three key objectives to enhance the applicability and effectiveness of the PICSOU framework's IEQ category. (1) It seeks to validate the modularization of the framework by testing its ability to assess IEQ in diverse campus environments, using data collected from Jincheng College in Chengdu, China. This validation process involves evaluating the framework's adaptability to varying spatial and operational conditions. (2) The study aims to explore the impact of real-time occupancy patterns on IEQ indicators, focusing on how dynamic occupancy influences factors such as air quality and thermal comfort. By analyzing these relationships, the study provides insights into optimizing IEQ in spaces with fluctuating occupancy levels. (3) The study seeks to develop a practical methodology for implementing the framework on large university campuses, ensuring its applicability and effectiveness across different contexts. By achieving these objectives, this work provides a comprehensive pathway for sustainable campus development that prioritizes occupant comfort while maintaining energy efficiency.

2.2 Methods

2.2.1 Project Site and Testing Setup

For this study, we chose Chengdu Jincheng College (CJC) as our project site. With a campus area of 1.4 km^2 that harbors a diverse range of indoor environments, including dormitories, classrooms, and offices, CJC is home to 31,000 students and 1771 teaching staff, making it an ideal testbed for evaluating IEQ across different spaces. The CJC campus is located in the city of Chengdu, the second largest city in Western China with a population of 21.4 million (2024). Characterized by a subtropical humid monsoon climate, Chengdu experiences distinct seasonal variations, with hot, humid summers and mild, damp winters. This climatic context presents unique challenges for IEQ management. During the IEQ testing, we collected real-time IEQ (CO_2, $PM_{2.5}$, temperature, relative humidity) and human presence data at a sampling interval of 1 min from 13 sensors installed in 6 dorms, 2 offices, 4 classrooms and outdoor across the CJC campus (see Fig. 2.1) throughout a 15-calendar-day period in December 2024.

成都锦城学院
CHENGDU JINCHENG COLLEGE

Fig. 2.1 Map of Chengdu Jincheng College with sensor locations

Winter was selected for monitoring due to (1) prevalent indoor cold stress in unheated spaces, (2) elevated $PM_{2.5}$ levels from reduced atmospheric dispersion, and (3) alignment with academic calendars to capture peak occupancy patterns, making it a critical period for IEQ assessment.

2.2.2 *Sensor Specifications and Installation*

For this study, we customized our sensors by integrating modules dedicated to specific IEQ indicators and human presence detection (FMCW) into one single sensor unit (see Table 2.1). All 13 sensors with the identical technical and physical specifications were installed in 13 unique locations across the campus, illustrations on spot of sensor installation within each typical indoor space are shown in Fig. 2.2.

2.2.3 *Data Processing Assumptions for Deciding Space Type-Specific IEQ Average and Occupancy Probability*

Over 1.9 million data points (13 datasets, each with 21,600 lines and 7 attributes) were measured and collected during the 15-calendar-day testing period. Although most of the data can be directly utilized for plotting time-dependent value change

Table 2.1 Sensor specifications

Device	Module	Accuracy	Resolution	Range
	CO_2	≤ ±40 ppm, ±3% of reading	1 ppm	0–9999 ppm
	$PM_{2.5}$	±10 μg@0–100 μg/m^3 ±10%@100–500 μg/m^3	1 μg/m^3	0–999 μg/m^3
	Temperature	≤ ±0.2 °C	0.1 °C	0–65 °C
	Relative humidity	≤ ±3%	0.1%	0–99%
	Occupancy (FMCW)	N/A	N/A	±60°, 6 m

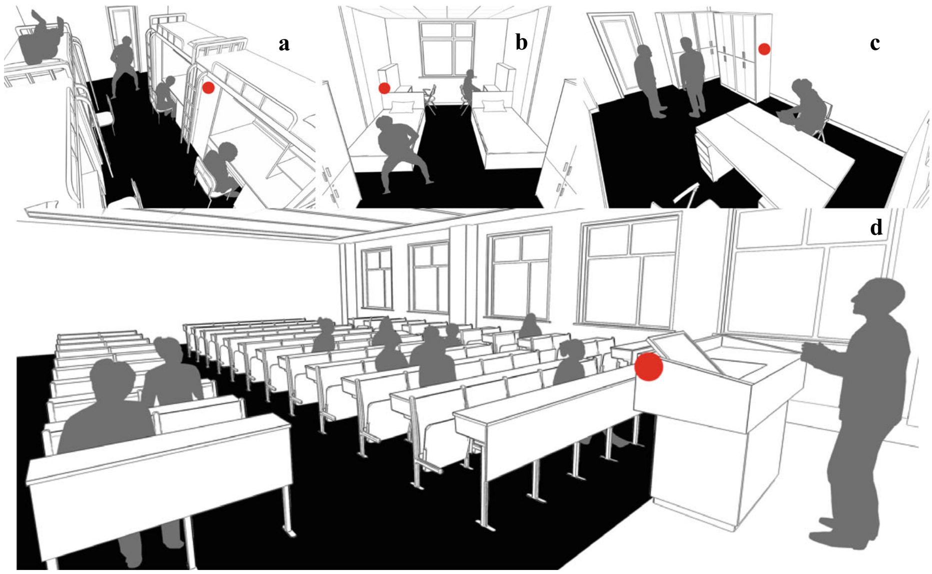

Fig. 2.2 Spot of sensor installation (marked by a red dot) in (**a**) 4-person dorms, (**b**) 2-person dorms, (**c**) offices and (**d**) classrooms

graphs without processing, we adopted the following assumption when processing data used for plotting each IEQ indicator's duration curve within each space type under different occupancy probabilities (see Eqs. 2.1 and 2.2).

$$\overline{X} = \frac{\sum_{i=1}^{n} (C_i/P_i/T_i/H_i) * D_i}{\sum_{i=1}^{n} D_i} \tag{2.1}$$

$\bar{X}$ is the average value of one of the four IEQ indicators (CO_2, $PM_{2.5}$, temperature and relative humidity) at a given time stamp within one of the three space types (dorm/office/classroom) represented by C_i, P_i, T_i and H_i. D_i is a binary value introduced as an error proofing mechanism designated as the *Denominator Contributor*, as a documented 6.28% of the total data were lost due to reasons such as mis-operation or/and accidental/unauthorized unplugging, in the event of an unpredicted data loss, D_i helps automatically adjust the number of properly functioning sensors so that the average value is always correctly solved for.

To solve for occupancy probability (defined as the percentage of occupied spaces within a space type), we adopted Eq. 2.2:

$$O_{drm/off/cls} = \frac{\sum_{i=1}^{n} P_i}{N_{drm/off/cls}} \tag{2.2}$$

where: $O_{drm/off/cls}$ is the occupancy probability at a given time stamp within one of the three space types (dorm/office/classroom), P_i is a binary value designated as the *Presence Detection Contributor*, $N_{drm/off/cls}$ is the total number of sensors dedicated to a specific space type. In this study, $N_{drm} = 6$, $N_{off} = 2$, $N_{cls} = 4$.

2.2.4 Identification of Critical IEQ Reference Values

Based on standards commonly referenced in China (Standardization Administration of China 2022; Architectural Society of China 2021), the EU (2019) and internationally (World Health Organization 2021), as well as recent findings on occupants' wellbeing (Lin et al. 2025) while taking into consideration the seasonal factor, we identified the following critical IEQ reference values (see Table 2.2), values highlighted in bold are used as threshold values for evaluating indoor environmental quality.

Table 2.2 Critical IEQ reference values

Issuer	Standard	CO_2, ppm	$PM_{2.5}$, μg/m^3	Temperature, °C	Relative humidity, %
China	GB/T 18883-2022	**1000**	**75** (24 h avg.)	Winter: **16**–24	Winter: 30–60
	T/ASC 02-2021	1000	35 (24 h avg.)	Winter: 20–26	Winter: 30–60
EU	EN 16798-1:2019	**I: 950**	N/A	**I: 21**–23	N/A
		II: 1200		**II: 20**–24	
		III: 1750		**III:** 19/**18**–25	
		IV: 1750		**IV: 17**–25	
WHO	AQG 2021	N/A	AQG: **5** **Interim** 4/3/2/**1**: 10/15/25/**35**	N/A	N/A

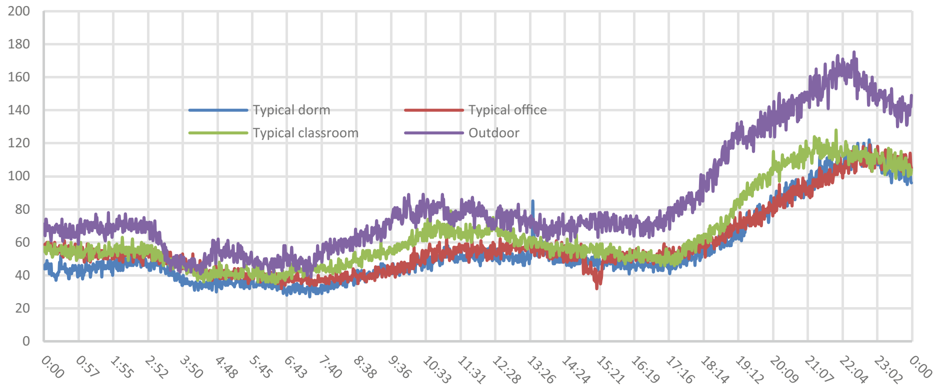

Fig. 2.3 Time-dependent $PM_{2.5}$ concentrations in a typical campus indoor space (dorm, office and classroom) and outdoor environment over a 24-h period (2024/12/23)

2.3 Results

2.3.1 Real-Time IEQ-Occupancy Interplay

As minimal validation of our research methodology and precursor to long-term testing and analysis using duration curves, we measured real-time $PM_{2.5}$ concentrations across typical indoor spaces (dormitory, office, classroom) and outdoor environments on a typical calendar day (December 23, 2024) to benchmark daily IEQ characteristics (see Fig. 2.3). The data reveal distinct temporal trends: e.g., indoor $PM_{2.5}$ concentrations in a typical classroom only mildly rose during occupancy hours (from 50 $\mu g/m^3$ at 8:00 to 72 $\mu g/m^3$ at 12:00 and dropped to 48 $\mu g/m^3$ at 17:00), exhibiting a pattern in directly correlated with outdoor $PM_{2.5}$ concentrations. In contrast, outdoor concentrations peaked in the evening (131–160 $\mu g/m^3$ between 20:00 and 22:00), likely due to reduced dispersion. These findings not only indicate infiltration challenges for naturally ventilated spaces, but also validate the necessity of high-resolution, short-term monitoring to identify occupancy-driven IEQ fluctuations before deploying long-term duration-curve analyses.

2.3.2 Seasonal Assessment of IEQ

To comprehensively evaluate the indoor environmental quality of all measured spaces, we analyzed the overall distribution of key IEQ indicators—CO_2, $PM_{2.5}$, and temperature within each space type. To this end, we plotted duration curves for these indicators during occupied hours and compared them against the applicable critical values outlined in Table 2.2 (see Fig. 2.4). This approach allowed us to systematically assess how frequently IEQ metrics exceeded or fell within acceptable thresholds, providing a robust understanding of spatial and temporal variations in environmental conditions. By focusing on occupied hours, we ensured that our analysis directly reflected the actual exposure of occupants.

Duration curves revealed stark IEQ variations across space types. Office W240 was the best-performing space, meeting CO_2 EU cat.I (100%), $PM_{2.5}$ CN limit (31%), and thermal comfort EU cat.I (70%). In contrast, classroom B313 performed the worst with 0% thermal comfort compliance for all thermal comfort standards and only 10% $PM_{2.5}$ CN limit compliance.

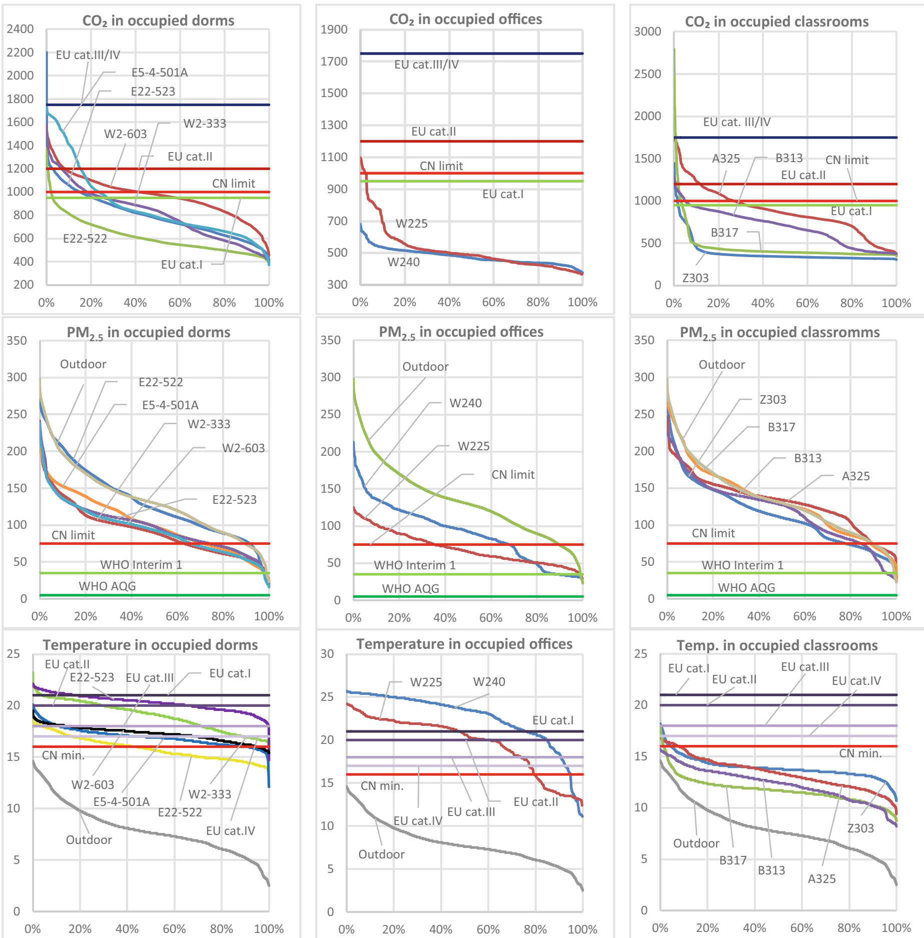

Fig. 2.4 Duration curve of CO_2, $PM_{2.5}$, and temperature in dorms, offices and classrooms during occupied hours

2.4 Discussion

2.4.1 CO_2, $PM_{2.5}$and Temperature Trends Across All Space Types

CO_2 Concentration Compliance: When considering 5% of occupied hours as an acceptable excess, offices met EU cat.I (950 ppm). Three out of four classrooms met EU cat.II (1200 ppm), while the last classroom only met EU cat.III, indicating that natural ventilation has been actively used with good results. Dormitories, with the higher values fell under EU cat.III (1750 ppm), reflecting challenges with natural ventilation in high-occupancy spaces.

$PM_{2.5}$ Level Compliance: $PM_{2.5}$ posed the most significant challenge across all measured spaces with the values exceeding for majority of the time CN limit (75 μg/m^3) and all WHO limits (AQG: 5 μg/m^3, Interim 1: 35 μg/m^3). These excessively high $PM_{2.5}$ values originated from outdoor air. Only offices exhibited somewhat lower indoor concentrations; all other space types closely followed outdoor concentrations with minimal difference. This highlights a clear drawback of natural ventilation: the inability to filter particles due to the absence of outdoor air filtration.

Thermal Comfort Compliance: The highest indoor temperatures were measured in offices, which also exhibited high temperature variability in a way that 10–20% of the time temperature was below the CN min. (16 °C) limit. Dormitories showed more stable temperatures, in which, five out of six dorms fulfilled the CN min. Classrooms were exceptionally cold and failed to comply about 90% of the occupied time with the CN min.

2.4.2 Best and Worst Space Type Based on Overall IEQ Performance

Best Overall IEQ: offices, which met CO_2 EU cat.I (950 ppm) for 95–100% of the occupied time, $PM_{2.5}$ CN limit (75 μg/m^3) for 30–70% of the occupied time, and thermal comfort EU cat.I (21 °C) for 48–75% of the occupied time. This performance is attributed to AC units providing controlled ventilation and heating.

Worst Overall IEQ: classrooms, with one particular classroom failed all thermal comfort thresholds (0% compliance) and another one meeting $PM_{2.5}$ CN limit (75 μg/m^3) for only 10% of the occupied time. Their reliance on natural ventilation and general lack of heating—a prevalent characteristic in the local subtropical climate—make classrooms particularly vulnerable to winter cold and outdoor $PM_{2.5}$ pollution.

2.4.3 Limitations

A key limitation of this study lies within its focus on winter conditions. In subtropical climates like Chengdu's, thermal comfort challenges in summer (e.g., overheating and high humidity) may exacerbate IEQ issues, particularly in naturally ventilated spaces. Future work should therefore incorporate multi-seasonal monitoring to comprehensively evaluate the year-round climate adaptability PICSOU's IEQ indicators.

2.5 Conclusions

This study advances the universality of the PICSOU framework by rigorously testing its Indoor Environmental Quality (IEQ) metrics in a subtropical monsoon climate, demonstrating its potential for climate-specific customization. Through high-resolution, real-time data collection across diverse indoor spaces, we identified notable deviations from temperate-climate benchmarks, particularly for temperature and $PM_{2.5}$ while relative humidity and CO_2 levels generally fulfilled EU criteria. A key finding is the critical role of $PM_{2.5}$, a parameter previously omitted from PICSOU as it was not a concern in mechanically ventilated spaces with outdoor air particle filters. The excessively high values of $PM_{2.5}$ in this study necessitate its inclusion for climates relying on natural ventilation. These findings highlight the need for climate-specific adaptations within PICSOU, as there is evidence supporting the use of lower temperature limits. Conversely, the results reveal a significant trade-off: natural ventilation responsively used by occupants with good CO_2 results posed a health risk due to the infiltration of polluted outdoor air, which cannot be cleaned without engaging particle filters. By modularizing the PICSOU framework, we demonstrate its scalability and adaptability to larger campuses and varied climates. This work not only strengthens PICSOU's theoretical foundation but also provides a practical pathway for its application in diverse environmental contexts. Future research should focus on refining these adaptive components and extending the framework's use to other climatic zones, ensuring its continued relevance in promoting sustainable campus development towards climate neutrality.

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Publication V

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Article

Parameter Optimization for Climate-Resilient IEQ Assessment: Validating Essential Metrics in the PICSOU Framework Across Divergent Climate Zones

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Abstract

To enhance the climate adaptability and diagnostic precision of university sustainability frameworks, this study presents a critical advancement to the PICSOU (Performance Indicators for Core Sustainability Objectives of Universities) framework's Indoor Environmental Quality (IEQ) module. The research employs a comparative approach across two distinct climate zones: the campus of Chengdu Jincheng College in a humid subtropical climate (CDJCC; Köppen Cwa) with natural ventilation, and the campus of Tallinn University of Technology in a temperate climate (TalTech; Köppen Dfb) with mechanical ventilation. A key innovation at CDJCC was the deployment of a novel, integrated sensor that combines a Frequency-Modulated Continuous Wave (FMCW) radar module for real-time occupancy detection with standard IEQ sensor suite (CO_2, $PM_{2.5}$, temperature, humidity), enabling unprecedented analysis of occupant-IEQ dynamics. At TalTech, comprehensive IEQ monitoring was conducted using standard sensors. Results demonstrated that mechanical ventilation (TalTech) effectively decouples indoor conditions from external fluctuations. In contrast, natural ventilation (CDJCC) exhibits strong seasonal coupling, reflected by a Seasonal Ventilation Efficacy Coefficient (λ_{season}), indicating that seasonal differences in effective ventilation are present but vary by indoor space type under occupied conditions. Consistent with this stronger indoor–outdoor linkage, $PM_{2.5}$ infiltration was also pronounced in naturally ventilated spaces, as evidenced by a high infiltration factor (I/O ratio) that remained consistently elevated. This work conclusively validates a conditional, climate-resilient workflow for PICSOU's IEQ category, integrating these empirical coefficients to transform its IEQ assessment into a dynamic and actionable tool for optimizing campus sustainability strategies globally.

Keywords: the PICSOU framework; indoor environmental quality; climate resilience; FMCW radar; occupancy-IEQ dynamics; natural ventilation; mechanical ventilation; university campus; sustainability

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1. Introduction

1.1. Current Status of Sustainability Assessment in University Campuses

University campuses, as core sites for knowledge innovation and talent development, hold significant strategic importance in global sustainable development and carbon emission reduction. University campuses typically contain large building stocks and complex end-use energy profiles [1–3]. Combined with high population density, these characteristics can make campuses a non-trivial contributor to urban carbon emissions [4–7]. Higher education institutions (HEIs) have increasingly contributed to carbon-neutrality agendas through systematic campus sustainability actions [5,8,9]. These actions commonly include green-campus programs, energy management, renewable energy deployment, and low-carbon mobility measures [1–3,6]. Beyond operational decarbonization, universities exert broader influence through education, research, and public engagement [7,10,11]. This institutional influence supports the diffusion of sustainability concepts and can shape pro-environmental social behaviors [5,6,12,13]. From a broader perspective, HEIs are now recognized as ideal testbeds for implementing the UN Sustainable Development Goals (SDGs), and are expected to embed sustainability principles into core strategies, curricula, and organizational culture rather than treating them as peripheral add-ons [7,12]. As forerunners of transformation, universities shape campus populations' habits and societal mindsets in ways that can either accelerate or impede sustainable development [7].

From an energy-systems perspective, university campuses operate as diversified, high-intensity loads within urban grids, combining laboratory baselines, extended-hours teaching spaces, residential services, and shared infrastructures (e.g., district heating). This end-use portfolio produces pronounced schedule-driven peaks alongside persistent baseloads, while long asset lifecycles and centralized procurement create path dependencies in HVAC, envelopes, and controls that lock in energy-use intensity and emissions trajectories for decades. At the same time, campuses offer distinctive potential for demand flexibility—load shifting, demand response, and progressive electrification of heat—provided interventions respect academic calendars and IEQ constraints. Consequently, credible governance must move beyond design intent toward measured performance: end-use disaggregation, weather-normalized baselines, occupancy-aware setpoints, and lifecycle cost analysis that links operational decisions to verifiable energy and carbon outcomes [14–16]. Recent zero-carbon campus action plans reinforce this perspective by explicitly treating campuses as a small-scale city model and proposing scalable frameworks for energy and emissions accounting that can be applied across campus types, geographies, and climatic contexts [17].

Assessment systems for university campuses have evolved from green building rating schemes such as LEED (Leadership in Energy and Environmental Design) and BREEAM (Building Research Establishment Environmental Assessment Method) [10,18,19] to sustainable campus ranking systems like UI GreenMetric and STARS (Sustainability Tracking, Assessment and Rating System) [20–22] and further to post-occupancy evaluation (POE) and real-time monitoring [23–27]. However, many frameworks rely on overly complex indicator sets and suffer from data inconsistency and limited comparability across institutions [4,28,29]. In addition, their adaptability across diverse space types and climatic contexts remains insufficient, which constrains generalizability [30–32]. Importantly, IEQ is often underweighted or treated in a largely static manner, limiting support for climate-resilient operations [10,33]. Among these, LEED and BREEAM primarily focus on individual building design, often falling short in covering overall campus operations and activities, and involve high implementation and data collection costs [10,34]. UI GreenMetric and STARS employ extensive indicator sets suffering from issues of data inconsistency and poor comparability, making it difficult to quantify actual carbon reduction

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contributions [20–22]. Moreover, their IEQ-related items are largely static and policy-oriented (e.g., the existence of guidelines or certifications) and provide little explicit guidance on how assessment criteria, thresholds, or weights should be adapted across different climate zones, which limits their practicality for climate-resilient campus operation [17]. General corporate or supply chain frameworks like ISO 14001 and Global Reporting Initiative (GRI) are not optimized for the unique structure and functions of HEIs [14,31]. Recent campus case studies in arid and Mediterranean climates further highlight that sustainability and IEQ strategies must be explicitly tailored to local climatic and cultural conditions rather than relying on globally uniform indicators, with social infrastructure, green space, and hybrid ventilation strategies all needing climate-responsive design [35,36].

Aiming to resolve the limitations from the above-mentioned tools, the diagnostic framework of PICSOU (Performance Indicators for Core Sustainability Objectives of Universities) was identified to measure carbon footprint and socio-economic performance through six categories comprising approximately 20 core indicators while balancing universality and local adaptability, thereby facilitating cross-institutional comparison and cost–benefit analysis. Its structure enhances comprehension and implementation for university administrators and enables the quantification of improvement measures. By prioritizing areas with significant greenhouse gas emissions and social impacts, the framework improves the targeting and effectiveness of emission reduction strategies, serving as a robust tool for advancing campus carbon neutrality and sustainable development [37].

1.2. The Core Role of IEQ in University Sustainability

With the global advancement of sustainable development and healthy campus initiatives, IEQ in university settings has become an interdisciplinary research focus spanning architecture, environmental science, and public health. University students and staff spend more than 80% of their daily time indoors, including dormitories, classrooms, laboratories, and libraries [38–40]. In these settings, air quality, thermal comfort, lighting, and acoustics can directly affect health, well-being, and learning-related outcomes [14,24,41,42]. Improving IEQ is not only a matter of building design but also a critical component of educational equity, public health, and sustainable development [14,39,43]. Recent studies have further strengthened this evidence base by explicitly linking IEQ conditions to cognitive performance, productivity, and health outcomes. Experimental and review work in offices shows that combinations of thermal, acoustic, visual, and air-quality parameters can significantly affect attention, task performance, creativity, and perceived comfort, and that moving conditions toward high-performance IEQ ranges yields measurable gains in cognitive functioning [44–48]. Qualitative and survey-based studies in HEIs likewise report that suboptimal thermal, acoustic, and air-quality conditions undermine concentration, emotional state, and learning processes, whereas better IEQ and human-centered or biophilic design strategies are associated with higher satisfaction, fewer symptoms, and enhanced perceived academic performance [49–52].

In parallel, dynamic and model-based IEQ assessment frameworks have emerged that treat the indoor environment as a time-varying system rather than a static condition. A representative example is the ALDREN TAIL scheme, which operationalizes IEQ rating by linking category levels to the fraction of (occupied) time that measured conditions remain within the corresponding boundaries. In this approach, higher-quality categories are awarded when exceedances beyond the target boundaries are sufficiently rare, providing a transparent bridge between time-resolved monitoring data and categorical compliance statements [53]. Deep learning and other advanced time series methods, initially developed for environmental and industrial process monitoring, have shown strong capabilities in capturing nonlinear dynamics and forecasting multi-variable quality indicators [54–57].

In the educational context, human-centric AIoT-based IEQ modeling has been proposed to integrate dense sensor networks with deep learning algorithms and multimodal occupant feedback, enabling the prediction of multidimensional IEQ conditions and their potential impacts on occupant wellbeing in real time [25]. These developments illustrate a broader shift towards data-driven, predictive, and adaptive IEQ management, and further emphasize the need for campus sustainability frameworks to better reflect dynamic, occupancy-aware, and climate-responsive IEQ performance rather than relying solely on static indicators.

Given the significant influence of IEQ on health, academic performance, and sustainable development of university campuses, the IEQ module of the PICSOU framework naturally constitutes a key focus of current research. In the EU policy context, the Commission's Technical Guidance for Technical Building Systems and Indoor Environmental Quality (EPBD recast; Articles 13, 23 and 24) emphasizes IEQ as an operational outcome supported by monitoring and inspection. The recommended core IEQ scope includes thermal conditions (e.g., indoor temperature), humidity, ventilation-related indicators (e.g., CO_2), and exposure to pollutants such as particulate matter (e.g., $PM_{2.5}$). Accordingly, the IEQ indicator set and reference categories adopted in this study (see Section 2.4.5) are designed to be consistent with this EU guidance, improving interpretability across building types and climate contexts [58].

However, the IEQ component of the PICSOU framework currently exhibits certain limitations. The IEQ section faces four main constraints:

1. In the selection of pollutant indicators, the PICSOU framework mainly emphasizes ventilation rates and thermal comfort, overlooking critical pollutants such as CO_2 and $PM_{2.5}$. Extensive reviews and empirical studies have demonstrated that these pollutants are closely linked to health, cognition, and comfort, and often exceed standards in university spaces, including dormitories and classrooms [14,15,18,24,59,60].
2. The use of static indicators in the PICSOU framework fails to capture dynamic processes such as actual occupancy, window-opening behaviors, and fluctuating occupant numbers. Research indicates that indoor air quality and thermal comfort are highly dependent on dynamic occupancy, ventilation behavior, and real-time control, particularly in high-density spaces like classrooms and dormitories where CO_2 concentration and $PM_{2.5}$ levels can fluctuate rapidly [14,16,25,59,61].
3. Developed initially for a temperate climate, the PICSOU framework has limited adaptability across diverse climate zones. Similar to many existing studies, IEQ research has predominantly focused on single regions, lacking multi-climatic zone validation and adaptability analysis [24,26,61,62].
4. The omission of distinctions among space types—such as dormitories, classrooms, and offices—in the PICSOU framework makes it difficult to address differentiated IEQ issues. Studies indicate that dormitories are prone to elevated CO_2 and $PM_{2.5}$; classrooms often experience CO_2 accumulation and inadequate thermal comfort. Different spaces therefore present distinct problems and optimization needs, requiring category-specific management and evaluation [23,24,27,43,62].

This study aims to address the current limitations of the PICSOU framework in IEQ assessment by: (1) expanding beyond the narrow range of pollutant indicators to comprehensively include key health and comfort factors such as thermal comfort, CO_2 and $PM_{2.5}$; (2) moving beyond static evaluation methods through the introduction of dynamic monitoring and real-time occupancy analysis; (3) transcending its temperate climate origins by validating its applicability in subtropical climatic conditions; and (4) refining space-type classifications such as dormitories, classrooms, and offices to better reflect campus environmental diversity.

Targeting these four issues, the study conducts a specific enhancement and optimization of the IEQ module within the PICSOU framework, incorporating multi-pollutant monitoring, dynamic assessment methods, cross-climate applicability, and space-type differentiation, thereby providing a more scientific, universally adaptable, and operationally viable pathway for sustainable campus development. The methodological workflow, from monitoring design to IEQ optimization, is illustrated in Figure 1

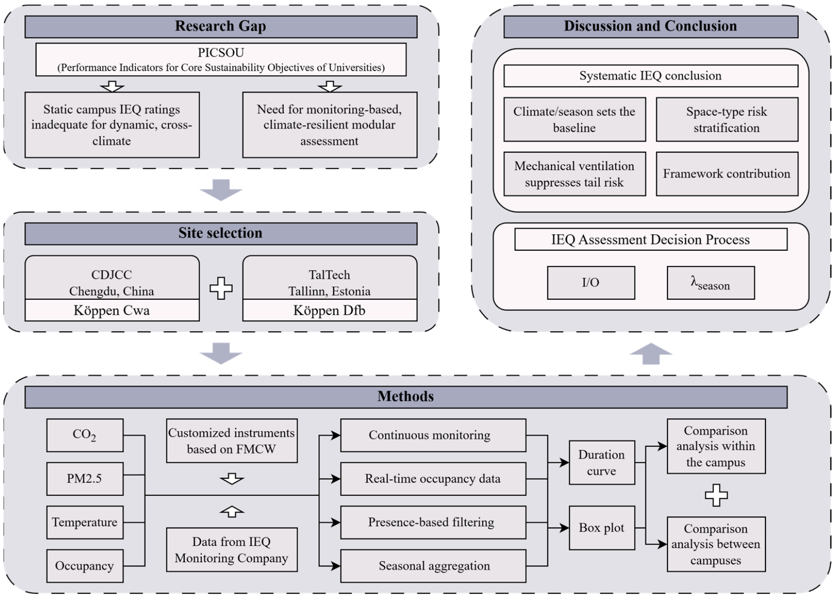

Figure 1. Graphical abstract of the study.

2. Materials and Methods

To establish the universality of the PICSOU framework across divergent climatic and cultural contexts, particularly in its IEQ category, a parallel IEQ monitoring campaign was conducted during the 2024–2025 academic year at two university campuses: Chengdu Jincheng College (CDJCC), China, and Tallinn University of Technology (TalTech), Estonia. The distinct environmental settings and methodological approaches employed at each site are summarized in Table 1, providing a foundational overview of the experimental design for the subsequent analysis.

Table 1. Overview of the experimental design.

Aspect	CDJCC Campus	TalTech Campus
Site Location	Chengdu, China	Tallinn, Estonia
Climate Zone	Subtropical monsoon climate	Temperate oceanic/continental climate
Monitoring Period	15 calendar days in autumn semester, 2024; 15 calendar days in spring semester, 2025	90 calendar days in autumn semester, 2024; 51 calendar days in spring semester, 2025
Space Types	Dormitories, classrooms, offices	Classrooms/auditoriums/meeting rooms, offices
Occupancy Tracking Method	FMCW radar module for real-time human presence detection	N/A

Table 1. *Cont.*

Aspect	CDJCC Campus	TalTech Campus
IEQ Parameters Measured	CO_2, $PM_{2.5}$, temperature, relative humidity	CO_2, $PM_{2.5}$, temperature, relative humidity
Data Resolution	1 min intervals for all parameters	10 min intervals for all parameters
Primary Focus	Validating IEQ under subtropical conditions, focusing on thermal comfort and $PM_{2.5}$ infiltration	Validating IEQ under temperate conditions, establishing baseline performance without occupancy influence
Connection to PICSOU	Field validation of the PICSOU's IEQ category in a non-Nordic context, highlighting need for climate-specific adaptations	Baseline validation of PICSOU's IEQ metrics under temperate climate in a pure mechanically ventilated context
Contribution to PICSOU	Demonstrated necessity for modular adjustments in PICSOU to account for regional challenges	Provided reference datasets for temperate climate zone, reinforcing PICSOU's core IEQ metrics without occupancy complexities
Unique Challenges	High humidity (70–80%), winter $PM_{2.5}$ peaks, lack of mechanical heating leading to cold stress	Standardized monitoring in controlled environments, but with potential gaps due to lack of occupancy correlation

2.1. Site Selection for Two Climate Zones

This study utilized locally available IEQ sensors to assess IEQ across the spring and autumn semesters at two sites—CDJCC and TalTech. The campuses lie in distinct climate zones, enabling cross-climatic conclusions of broader applicability.

2.1.1. CDJCC

Chengdu Jincheng College (CDJCC) is located in Pidu District, Chengdu—the fourth largest city in China, with a population of 21.4 million as of Q2 2025. Located in a subtropical monsoon climate (Cwa in the Köppen climate classification), the metropolis of Chengdu has distinct seasons characterized by hot, rainy summers, mild, damp winters and persistently high humidity. The CDJCC campus harbors 31,000 students and 1771 teaching staff, covers approximately 1.4 km^2 and includes a variety of indoor environments such as dormitories, classrooms, and offices. Ventilation operates in mixed-mode, consisting mostly of natural ventilation with supplemental air-conditioning running during summer and winter months when thermal comfort cannot be maintained.

During the autumn semester, we deployed 13 sensors across 6 dormitories, 2 offices, 4 classrooms, and 1 outdoor location. During the spring semester, we adopted a mostly identical sensor deployment scheme (changed only two office locations due to limited accessibility during the testing period) with 1 additional outdoor location for enhanced verification of outdoor air quality (Figure 2). In both the spring and autumn semesters, data were sampled at 1 min intervals, capturing real-time IEQ parameters including CO_2, $PM_{2.5}$, temperature, and relative humidity. Each semester comprised 15 days of measurements, accompanied by synchronized records of occupant presence detected by the same IEQ sensor at each location.

2.1.2. TalTech

Tallinn University of Technology (TalTech) is located in Tallinn, the capital of the Republic of Estonia. Situated on the country's north coast, Tallinn has a population of approximately 440,000, the largest in the nation. The city sits in the transitional zone between temperate oceanic climate and temperate continental climate (Dfb in the Köppen climate classification)—mild and humid year-round, with evenly distributed precipitation, and significant differences in daylight hours between seasons thanks to its high latitude.

The university occupies 29 buildings with a total floor area of 108,312 m^2, serving 9100 students, 1240 faculty members and 1002 staff as of Q4 2024. Mechanical ventilation is used year-round across the campus; systems operate continuously, and district heating is activated during cold months (normally lasts from 1 October to 31 March; exact start and end dates may vary depending on weather conditions).

Leveraging the widespread deployment of permanently installed sensors on campus, we compiled a dataset from 13 sensors—7 classrooms/auditoriums/meeting rooms, 4 offices, and 2 outdoor locations (Figure 3) over extensive periods throughout the academic year. Measurements were logged at 10 min intervals, capturing core IEQ parameters: CO_2, $PM_{2.5}$, temperature and relative humidity. Due to the absence of an occupancy detection module within the sensors, no real-time records of occupant presence were documented on the TalTech site.

Figure 2. Map of CDJCC with sensor locations.

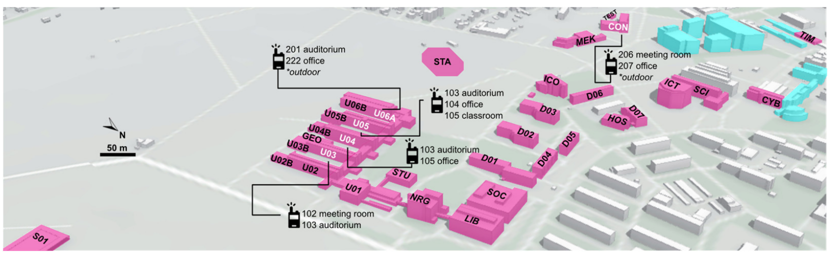

Figure 3. Map of TalTech with sensor locations.

2.2. Sensors Specifications

2.2.1. Sensors at CDJCC

On the CDJCC site, we custom-built sensor units by integrating dedicated modules for IEQ measurement with human presence detection based on frequency-modulated continuous-wave (FMCW) radar into a single device. All sensors shared identical parameters and specifications (Table 2). Installation locations in representative space types (4-person dormitory, 2-person dormitory, office and classroom) are shown in Figure 4.

Table 2. CDJCC sensor specifications.

Device	Model	Module	Accuracy	Resolution	Range
	air quality monitor AN-PCT (Rmikey PCB Co. Ltd., Shenzhen, China)	CO_2	≤± 40 ppm, ±3% of reading	1 ppm	0–9999 ppm
		$PM_{2.5}$	±10 μg @ 0–100 μg/m^3 ±10% @ 101–500 μg/m^3	1 μg/m^3	0–999 μg/m^3
		Temperature	≤± 0.2 °C	0.1 °C	0–65 °C
		Relative Humidity	≤± 3%	0.10%	0–99%
		Occupancy (FMCW)	N/A	N/A	±60 degrees, 6 m

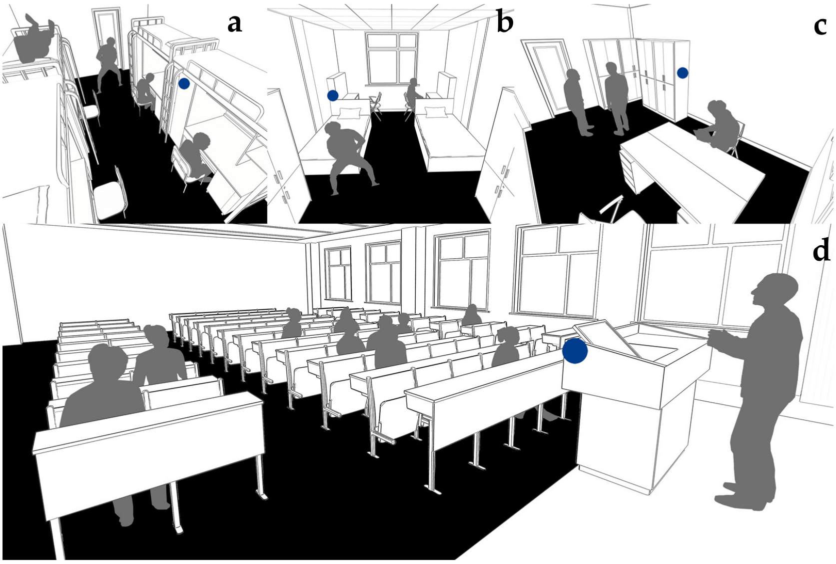

Figure 4. CDJCC sensor layout in typical space types: (**a**) 4-person dorms, (**b**) 2-person dorms, (**c**) offices, (**d**) classrooms.

2.2.2. Sensors at TalTech

On the TalTech site, IEQ monitoring is outsourced to specialized industrial partner. All sensors shared identical parameters and specifications; sensor specifications are summarized in Table 3, and installation locations in representative space types (meeting room/classroom/auditorium and office) are shown in Figure 5.

Table 3. TalTech sensor specifications.

Device	Model	Module	Accuracy	Resolution	Range
	airPurity indoor climate monitoring sensor (Thinnect OÜ, Tallinn, Estonia)	CO_2	≤± 40 ppm, ± 3% of reading	1 ppm	10–40,000 ppm
		$PM_{2.5}$	±10 μg @ 0–100 μg/m^3 ±10% @ 101–1000 μg/m^3	1 μg/m3	0–1000 μg/m^3
		Temperature	≤± 0.8 °C	0.1 °C	−10–60 °C
		Relative Humidity	≤± 6%	0.10%	0–100%

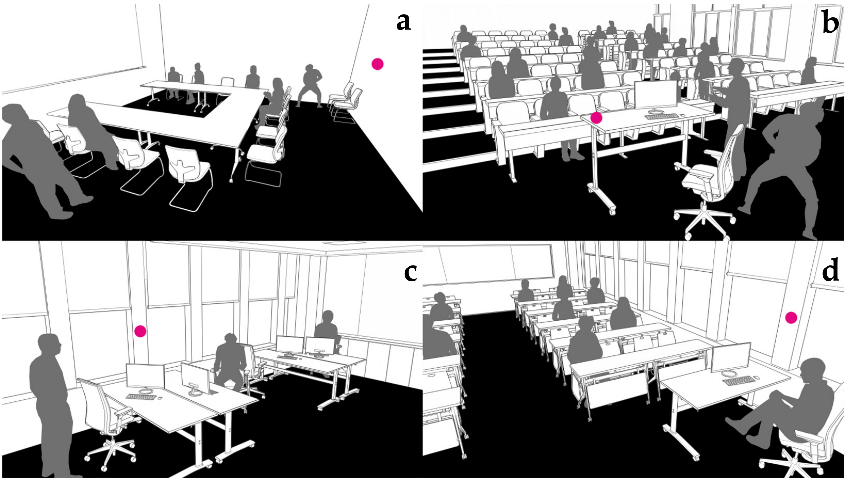

Figure 5. TalTech sensor layout in typical space types: (**a**) meeting rooms, (**b**) auditoriums, (**c**) offices, (**d**) classrooms.

2.3. Data Collection and Preparation

2.3.1. Data-Period Designation

This study compares campus IEQ performance under different ventilation modes within various climate zones. Accordingly, we analyzed monitoring data from representative autumn and spring semesters at two universities.

At CDJCC, the typical autumn semester (September–January) and spring semester (February–June) were each monitored for 15 days (during the autumn semester: 17 December–31 December; during the spring semester: 9 May–23 May). In total, we collected over 3.8 million records, comprising 13 datasets in autumn semester and 14 datasets in spring semester, with each dataset containing 21,600 time-steps and 5 attributes (CO_2, $PM_{2.5}$, temperature, relative humidity and real-time occupancy status).

At TalTech, the typical autumn semester runs September–December and the spring semester February–June. For analysis, in order to fully overlap with teaching activities and the district-heating run time, we defined a winter period of 22 September–20 December, we also defined a summer period of 2 May–21 June to coincide with teaching and mechanical cooling, the period between January and April was omitted as it is the extended heating season during the spring semester. We compiled over 1.52 million records in total, spanning 55 spring datasets and 65 autumn datasets, where each dataset contained a single-indicator time series.

2.3.2. Data Processing

Prior to conducting the comparative analysis, we subjected all raw monitoring data from the two campuses to systematic cleaning and structural preprocessing to ensure temporal completeness and the reliability of subsequent statistical procedures.

For the CDJCC dataset, where each exported record contains multiple monitored parameters associated with a single timestamp, a complete 1 min time series was first generated for each designated monitoring period. All collected records were then Boolean-matched to this full-period sequence to ensure accurate alignment at every time point. Based on the aligned data, we further quantified the overall data coverage separately for the spring (corresponding to the summer monitoring period) and autumn (corresponding to the winter monitoring period) semesters. In the spring semester, 302,400 theoretical timestamps were expected, among which, 273,461 valid entries were recorded and 28,939 were missing, yielding a loss rate of 9.57%. In the autumn semester, 280,800 timestamps were expected, with 263,175 valid entries and 17,625 missing, corresponding to a loss rate of 6.28%. Most lost points were attributed to accidental sensor power interruptions or operational mishandling. To avoid artificial smoothing effects that could bias the interpretation of tail behavior in duration-curve analysis, all missing values were retained as NaN without interpolation or model-based reconstruction.

The TalTech dataset differs fundamentally from CDJCC in structure, as each timestamp corresponds to only one IEQ parameter, forming a set of single-indicator time series. Based on the three key parameters required for subsequent analysis (CO_2, $PM_{2.5}$, and temperature), all relevant records were extracted from the operator-provided database for both the winter (corresponding to the autumn semester) and summer (corresponding to the spring semester) monitoring windows, and the seasonal data availability was quantified accordingly. The results reveal substantial seasonal and inter-indicator variation in data coverage. During the winter monitoring period, the loss rates were 26.82% for $PM_{2.5}$, 22.34% for CO_2, and 22.33% for temperature. In contrast, during the summer monitoring period, the loss rates were significantly lower, amounting to 4.87% for $PM_{2.5}$, 4.99% for CO_2, and 4.99% for temperature. These missing values reflect the intrinsic recording limitations of the single-indicator monitoring system across seasons and parameters; therefore, all missing points were retained as NaN, without interpolation, so as to preserve the true coverage profile of each indicator.

Regarding extreme-value handling, all extreme observations were retained in the dataset rather than being removed. High or low IEQ values typically correspond to meaningful transient conditions—such as CO_2 accumulation under high occupancy, $PM_{2.5}$ ingress during window-opening events, or short-term ventilation or infiltration fluctuations—and thus contain valuable diagnostic information. Because the duration curve is a central analytical tool in this study, and its interpretive power relies on retaining the full distribution, especially the upper and lower tails, discarding extreme values would directly weaken its ability to characterize the frequency and persistence of exceedances. It should also be noted that box plots were constructed using the 1.5 $\times$ IQR rule, which suppresses the display of outliers; therefore, retaining extreme values does not affect box-plot readability but is essential for ensuring accurate duration-curve-based assessments.

2.4. Analytical Method

2.4.1. Duration Curve

A duration curve (also called a duration–exceedance curve) orders a variable from high to low over the observation period and plots the proportion (or probability) of time the variable exceeds a given value, thereby providing an intuitive view of its distribution across time using Equation (1).

$$P(X \geq x_i) = \frac{m}{N+1} \tag{1}$$

Here, X denotes the monitored indicator (e.g., $PM_{2.5}$ level or CO_2 concentration); x_i is the ith observation after sorting; m is the number of samples greater than or equal to that observation; and N is the total number of observations. Using $N + 1$ avoids boundary probabilities of 0 or 1 and yields a more reasonable exceedance distribution. This probability reflects the share of time during which the indicator exceeds a given value and is used to plot the duration curve, thereby revealing the occurrence frequency of different concentration levels and their persistence over the monitoring period.

In this study, we applied the duration curve method to analyze three IEQ parameters—CO_2 concentration, $PM_{2.5}$ level, and temperature—separately for the spring and autumn semesters to reveal seasonal differences. For each parameter, observations collected during occupied periods were first filtered and then sorted from high to low; the corresponding exceedance probabilities were calculated to construct the duration curve. This approach statistically characterizes the relationship between a variable's magnitude and the percentage of time it is equaled or exceeded, providing an intuitive view of the distribution and persistence of indoor air quality over time and facilitating the identification and comparison of extremes.

2.4.2. Occupancy Probability

The custom-built sensor units deployed at CDJCC are capable of monitoring IEQ data and real-time human presence simultaneously thanks to their multi-modular configuration. Since there has been no widely documented precedent of a single, integrated device that combines an FMCW radar module with a standard IEQ sensor suite (CO_2, $PM_{2.5}$, temperature, relative humidity) for simultaneous monitoring, it is crucial to conduct a comprehensive verification of the reliability of the FMCW radar module within the sensors. To this aim, in addition to examining the continuity of the time-stamped occupancy data, we also adopted the dimensionless quantity of occupancy probability to be used together with duration curves to better observe the correlation between the average IEQ values within a space type and the overall occupancy of the same space type. At any given timestamp, occupancy probability is designated as the proportion of the total number of occupied rooms over the total number of rooms within the same space type. For example, a 0.5 occupancy probability in classrooms denotes that human presence is detected in half of all the classrooms at the timestamp of observation. To solve for occupancy probability, we adopted Equation (2):

$$O_{drm/off/cls} = \frac{\sum_{i=1}^{n} O_i}{N_{drm/off/cls}} \quad (2)$$

in which, $O_{drm/off/cls}$ is the occupancy probability at a given timestamp within one of the 3 space types at CDJCC (dormitory/office/classroom), n is the number of rooms with detected human presence within a specific space type, O_i is a binary value designated as the *Occupancy Detection Contributor*, when O_i = 1, human presence is detected in a room, when O_i = 0, no human presence is detected in a room. $N_{drm/off/cls}$ is the total number of sensors dedicated to a specific space type. At CDJCC, N_{drm} = 6, N_{off} = 2, N_{cls} = 4.

To solve for the average IEQ value within a space type at a given timestamp, we adopted Equation (3):

$$\overline{X} = \frac{\sum_{i=1}^{N_{drm/off/cls}} (C_i/P_i/T_i/H_i) * D_i}{\sum_{i=1}^{N_{drm/off/cls}} D_i} \quad (3)$$

in which $\overline{X}$ is the average IEQ value from one of the 4 IEQ indicators (CO_2, $PM_{2.5}$, temperature and relative humidity) at a given timestamp within one of the 3 space types (dorm/office/classroom) represented by C_i, P_i, T_i and H_i. $N_{drm/off/cls}$ has the same definition as in Equation (2). D_i is a binary value introduced as an error-proofing mechanism designated as the *Denominator Contributor*. When D_i = 1, a sensor is functioning as intended and IEQ data is documented, whereas D_i = 0 denotes a mishap with no data documented. Verification of reliability of the FMCW radar module was carried out during the autumn semester's monitoring period at CDJCC, from which, a documented 6.28% of the total data were lost due to reasons such as mis-operation or/and accidental/unauthorized unplugging, in the event of an unpredicted data loss, D_i helps automatically adjust the number of properly functioning sensors so that the average IEQ value is always correctly solved for.

2.4.3. Box Plot

Coined in 1977, box plot is a nonparametric visualization based on the five-number summary. It displays the minimum, maximum, median, and the lower and upper quartiles. It is used to describe the central tendency and dispersion of numerical data and to identify outliers [63].

For IEQ indicators such as $PM_{2.5}$ level and CO_2 concentration, box plots require no normality assumption and, in the presence of skewness and short-lived peaks, provide a robust way to compare typical levels and anomalous fluctuations across different spaces, periods, or operating conditions. Relevant equations are as follows (see Equations (4)–(11)):

$$x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(n)} \tag{4}$$

$$Q_1 = quantile(x, 0.25) \tag{5}$$

$$Q_2 = median(x) \tag{6}$$

$$Q_3 = quantile(x, 0.75) \tag{7}$$

$$IQR = Q_3 - Q_1 \tag{8}$$

$$L_{fence} = Q_1 - 1.5\,IQR \tag{9}$$

$$U_{fence} = Q_3 + 1.5\,IQR \tag{10}$$

$$outlier\ if\ x_i < L_{fence}\ or\ x_i > U_{fence} \tag{11}$$

here, Q_1 is the lower quartile (25%), the median Q_2 is at the 50%, and the upper quartile Q_3 is at the 75%. The interquartile range $IQR = Q_3 - Q_1$ describes the dispersion of the middle 50% of the data. L_{fence} and U_{fence} denote the whisker ends, the minimum/maximum observations. Outside the range of $[L_{fence}, U_{fence}]$ is classified as an outlier.

To characterize IEQ across climate zones, seasons, and space types and to enable macro-level comparisons, this study employs box plots using Tukey's $1.5 \times IQR$ rule—with whiskers limited to $Q_1 - 1.5IQR$, $Q_3 + 1.5\,IQR$—to estimate typical levels and thereby reveal overall differences among spaces. Applying the $1.5 \times IQR$ criterion provides a more precise view of central tendency and spread for the overall picture. In view of inevitable extremes, outliers are not displayed to improve readability; these conditions are instead depicted using duration curves.

2.4.4. Occupation Determination

In this study, occupied periods at CDJCC were identified using the instruments' built-in presence-detection module, which labeled the occupant-presence status at the corresponding timestamps.

In the campus buildings of TalTech, occupant presence was primarily inferred from the CO_2 time series. Outdoor CO_2 background levels typically fluctuate slightly within a narrow range; indoors, since human respiration is the main CO_2 source, a pronounced rise in CO_2 concentration within a given time window generally indicates that the space is occupied. Conversely, if the concentration remains stable or declines, the space is considered unoccupied. Indoor CO_2 is also affected by mechanical-ventilation operation and outdoor-background variability, and the collection of time-series data is subject to sensor acquisition delays, leading to a lag in the data timestamps relative to actual occupancy.

Based on the above principles, the collected time-series data can be analyzed using Equations (12) and (13) to determine whether occupants were present at each time step.

$$\Delta C(t) = C(t) - C(t-1) \tag{12}$$

$$O(t) = \begin{cases} 1, & \text{if } \Delta C(t) > 0 \text{ } and \text{ } C(t) > 550 \\ 0, & otherwise \end{cases} \tag{13}$$

In this formulation, let $\Delta C(t)$ denote the CO_2 concentration at time t. The increment between adjacent time steps is defined as $\Delta C(t) = C(t) - C(t-1)$. On this basis, we construct an occupancy indicator $O(\mathrm{t})$: assign "$O(t) = 1$" if and only if $\Delta C(t) > 0$ and $C(t) > 550$; otherwise assign "$O(t) = 0$". This rule emphasizes increases relative to the preceding time step and incorporates an absolute threshold to reduce the risk of misclassification.

2.4.5. Identification of Critical IEQ Reference Values

Based on commonly used Chinese standards [64,65], relevant EU standards [66], and international standards [67]—together with recent findings on occupant health and comfort—and using the summer and winter thresholds specified in these standards, we determined the following key IEQ reference values (see Table 4). This selection of core IEQ indicators and the category-based interpretation is also consistent with the EU Commission's technical guidance on indoor environmental quality monitoring and assessment under the EPBD recast [58]. Values highlighted in bold are the thresholds used as benchmarks for the IEQ assessment in this study.

Table 4. Critical IEQ reference values.

Semester	Issuer	Standard	CO_2, ppm	$PM_{2.5}$, μg/m^3	Temperature, °C	Relative Humidity, %
Spring	China	GB/T 18883-2022 [64]	**1000**	**75** (24 h avg.)	Summer: 22–**28**	Summer: 40–80
		T/ASC 02-2021 [65]	1000	35 (Max. 5 days/1 y) or 15(1 y avg.)	N/A	N/A
	EU	EN 16798-1:2019 [66]	**I: 950**	N/A	**I**: 23.5–**25.5**	N/A
			II: 1200		**II**: 23–**26**	
			III: 1750		**III**: 22–**27**	
			IV: 1750		**IV**: 21–**28**	
	WHO	AQG 2021 [67]	N/A	AQG: **5** **Interim** 4/3/2/**1**: 10/15/25/**35**	N/A	N/A
Autumn	China	GB/T 18883-2022 [64]	**1000**	**75** (24 h avg.)	Winter: **16**–24	Winter: 30–60
		T/ASC 02-2021 [65]	1000	35 (Max.5 days/1 y) or 15(1 y avg.)	N/A	N/A
	EU	EN 16798-1:2019 [66]	**I: 950**	N/A	**I**: **21**–23	N/A
			II: 1200		**II**: **20**–24	
			III: 1750		**III**: 19/**18**–25	
			IV: 1750		**IV**: **17**–25	
	WHO	AQG 2021 [67]	N/A	AQG: 5 Interim 4/3/2/**1**: 10/15/25/**35**	N/A	N/A

2.4.6. T-Distribution Confidence Intervals for Key Room-Level Indicators

In this study, Student's t-distribution (Equation (14)) [68,69] is used in an estimation framework to quantify the uncertainty of two key conclusions, rather than solely for classical null-hypothesis significance testing. For each campus–season–space-type combination, room-level indicators, namely the seasonal CO_2 ratio λ_{season} and the room-level $PM_{2.5}$ I/O ratio, are treated as independent observations. Within each group, the parameter of interest is the mean value of the room-level indicator, and its 95% confidence interval is constructed using the t-distribution.

Specifically, for a generic room-level indicator x, the 95% confidence interval for the group mean is given by

$$\overline{x} \pm t_{0.975,n-1} \frac{s}{\sqrt{n}} \quad (14)$$

where $\overline{x}$ is the sample mean across rooms, s is the sample standard deviation between rooms, n is the number of rooms (or sensor points) in the group, and $t_{0.975,n-1}$ is the two-sided 97.5th percentile of Student's t-distribution with $n - 1$ degrees of freedom. This formulation explicitly accounts for the fact that the population variance is unknown and must be estimated from the sample, which is particularly important given the relatively small number of rooms in some campus–space-type groups.

The resulting t-distribution confidence intervals are then used to examine whether the empirically observed room-level indicators are consistent with the two main conclusions of this study (regarding the seasonal CO_2 ratios λ_{season} and the $PM_{2.5}$ I/O behavior), following current recommendations that emphasize estimation and interval interpretation rather than reliance on point estimates or p-values alone [69].

3. Results

3.1. Reliance Verification of CDJCC Sensors' FMCW Radar Module

We conducted reliance verification on the FMCW radar module from custom-built sensors used at CDJCC during the autumn semester's monitoring period by plotting the duration curve of each space type's average CO_2 value under different occupancy probabilities (see Figure 6).

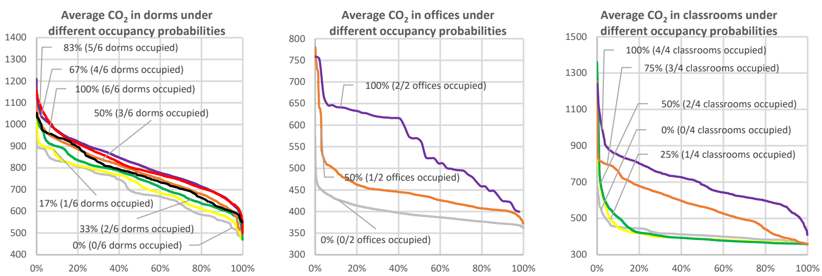

Figure 6. Average CO_2 in different space types under different occupancy probabilities.

Figure 6 indicates a positive correlation between average CO_2 concentration and occupancy probability across all space types, which aligns with the established principle that CO_2 level serves as a reliable proxy for human presence, although such correlation can be coincidental and does not necessarily suggest any direct causality between increased occupancy probability and increased average CO_2 value of occupied rooms within the same space type, as each occupied room's peak CO_2 value can greatly vary due to ventilation efficiency and occupant behavior, the fact that all non-zero occupancy probabilities' duration curves appear above that of the 0% occupancy probability suggests that the

FMCW radar module: (1) was not producing grossly incorrect occupancy detection results; (2) produced occupancy detection that was at least directionally correct (occupied rooms have higher average CO_2 value than empty ones); (3) was not systematically misclassifying occupancy in a way that violates such fundamental physical relationship. Additionally, an anomaly is observed in dormitories, where the duration curves for 83% and 67% occupancy probabilities largely overlap and exceed the curve for 100% occupancy probability. This inverse relationship can be attributed to the small spatial volume of dormitories; higher occupancy probability increases the probability of door or window opening for natural ventilation, thereby reducing CO_2 accumulation. In contrast, larger spaces like offices and classrooms exhibit a stronger positive correlation, void of such anomaly, likely due to reduced ventilation interventions stemming from social inhibition among occupants. The overall realism of the duration curves validates the synchronous data collection of the FMCW radar module and its IEQ suite counterpart, confirming that the FMCW radar module was working as intended.

To further assess the methodological comparability between the FMCW radar-based occupancy detection at CDJCC and the CO_2-based occupancy inference used at TalTech, we conducted a targeted cross-validation using the CDJCC dataset. The analysis was restricted to the same space types as at TalTech, namely offices and classrooms, and to periods in the spring and autumn semesters when both FMCW radar–derived occupancy flags and indoor CO_2 measurements were simultaneously available. On this subset of data, we reproduced the TalTech rule-based occupancy model exactly: a room is classified as “occupied” if the indoor CO_2 concentration remains above 550 ppm over a 10 min interval, and the resulting binary occupancy status is inferred solely from the CO_2 time series without using any radar information. The CO_2-based occupancy labels were then temporally aligned with the FMCW-based occupancy labels, and all time steps with both labels available were used to quantify their agreement.

The cross-validation results can be summarized in two main points. For clarity, we report the summary statistics in Table 5 and illustrate two representative episodes in Figure 7.

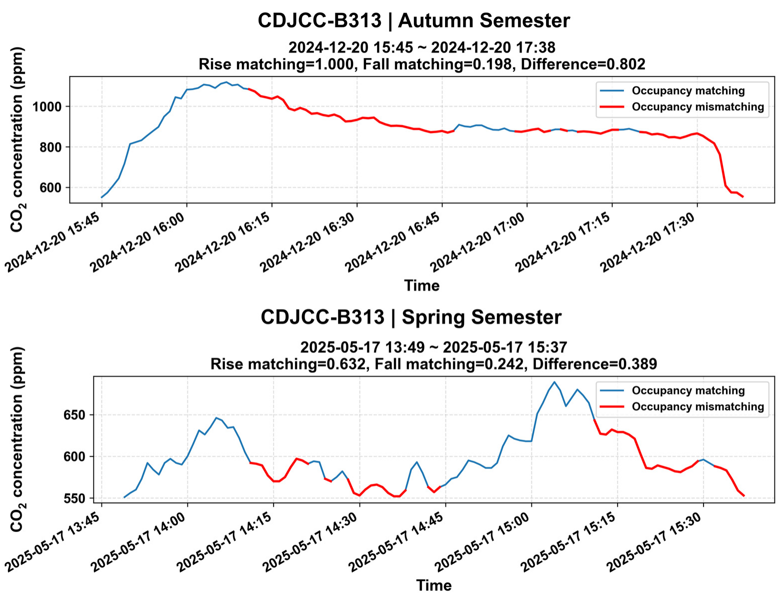

Figure 7. Representative CO_2 concentration cycles used to illustrate the methodological comparability between radar-based and CO_2-based occupancy detection.

Table 5. Cross-validation of CO_2-based occupancy inference against FMCW-based occupancy detection at CDJCC for spring and autumn semester datasets.

Metric	Spring-Semester Dataset	Autumn-Semester Dataset	Spring + Autumn Combined
Number of rows with CO_2-based occupancy prediction	18,396	7681	26,077
Fraction of predicted rows in growing phase	0.483	0.449	0.473
Fraction of predicted rows in decaying phase	0.517	0.551	0.527
Number of matching rows (prediction = FMCW)	11,177	4765	15,942
Matching ratio	0.608	0.62	0.611
Matching in growth phase	0.752	0.776	0.758
Matching in decay phase	0.473	0.494	0.479

First, during “standard growing phases” of CO_2 (i.e., periods when indoor CO_2 exhibits a sustained increase without pronounced reversals), the CO_2-based occupancy estimates derived from the TalTech rule show a high level of agreement with the FMCW-based occupancy labels at CDJCC. This indicates that, for typical situations in which occupants enter the room and remain there for some time so that indoor CO_2 accumulates monotonically, the CO_2-based inference and the radar-based detection identify occupied states in a broadly comparable manner. These phases form the core of the clearly occupied periods that underpin the cross-campus analysis in this study.

Second, once indoor CO_2 no longer increases monotonically but instead exhibits plateaus, declines, or repeated oscillations, discrepancies between the two methods become much more pronounced. Under the mixed-mode ventilation conditions at CDJCC, window opening, door opening, and short absences tend to dilute indoor CO_2, so that even when people are still present, CO_2 may temporarily decrease or fluctuate substantially; when the number of occupants is small or the occupancy level varies rapidly, indoor CO_2 can also remain at comparatively low levels for extended periods. Because the TalTech rule requires CO_2 to remain above 550 ppm and to display a rising tendency over the 10 min interval, such “occupied but CO_2-decreasing or low-CO_2” episodes are systematically classified as “unoccupied” and thus omitted from the CO_2-based occupancy record. It should be noted that, although TalTech employs a purely mechanical ventilation system and therefore tends to exhibit smoother and more nearly linear CO_2 buildup during occupancy, periods with few occupants or rapidly changing occupancy can still produce oscillations or short-term decreases in CO_2, which are likewise prone to being excluded as “unoccupied” under the same rule.

Taken together, these findings suggest that the two campuses are methodologically comparable with respect to clearly occupied periods characterized by sustained CO_2 buildup: in such intervals, the TalTech CO_2-based method and the CDJCC FMCW-based detection provide consistent “occupied” classifications, and our cross-campus comparisons are intentionally based primarily on this robust subset of occupied states. Consequently, the moderate overall matching ratio reported in Table 5 should not be interpreted as low FMCW radar accuracy, but rather as a reflection of the conservative nature of the CO_2-based inference, which systematically excludes certain occupied intervals by design. At the same time, the cross-validation also reveals that the current TalTech CO_2-based approach structurally omits part of the occupancy dynamics, specifically those situations in which people are present but indoor CO_2 decreases or remains low due to strong ventilation or low occupant density. From a methodological standpoint, complementing CO_2-based inference with non-intrusive, direct occupancy sensing technologies such as FMCW radar in TalTech-type settings would enable a more complete representation of occupied periods spanning both CO_2 accumulation and decay phases, and would further strengthen the robustness of cross-campus occupancy comparisons.

3.2. Spring–Autumn Semester Comparisons for Each Campus

In this comparative analysis, the portion from Q_1 to Q_3 in the box plots represents the middle 50% of the data for each room type, reflecting the general IEQ level under typical conditions; we refer to this as the "typical interval." The upper and lower whiskers represent the fluctuation range of IEQ indicators under special conditions for each space type, referred to here as the "extreme-value interval."

In this study, the large data volume produced too many outliers in the box plots, making them difficult to read. The duration curve compensates for this limitation by more completely displaying each room's special behavior during occupied periods.

3.2.1. Spring–Autumn Semester Comparisons at CDJCC

- CO_2

In the spring semester at CDJCC (Figures 8–10 and Table 6), the median CO_2 concentrations for dormitories/offices/classrooms/outdoors were 913/489/552/419 ppm, with the median ranking from high to low being dormitories > classrooms > offices. The typical CO_2 concentrations (box range) in dormitories exceeded the EU cat. II summer limit of 1200 ppm in 2% of cases; by contrast, those for all other space types remained below their respective standard thresholds. Dormitories and classrooms showed relatively long box ranges, which indicates larger typical fluctuation. When interpreted in conjunction with the duration curves, the results indicate that, in the spring semester, CO_2 concentrations in dormitories and classrooms exhibit larger typical fluctuations with occasional extreme values.

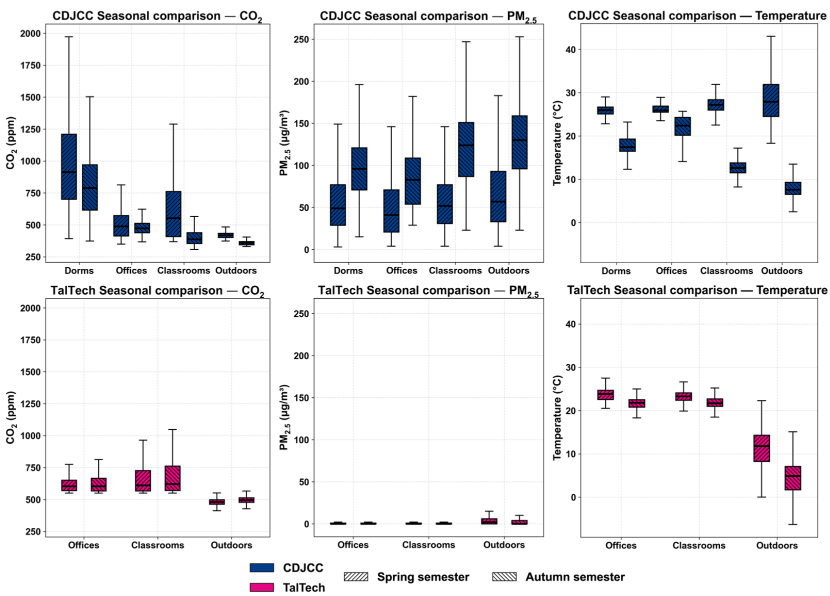

Figure 8. CDJCC and TalTech: same room type, within-campus spring vs. autumn.

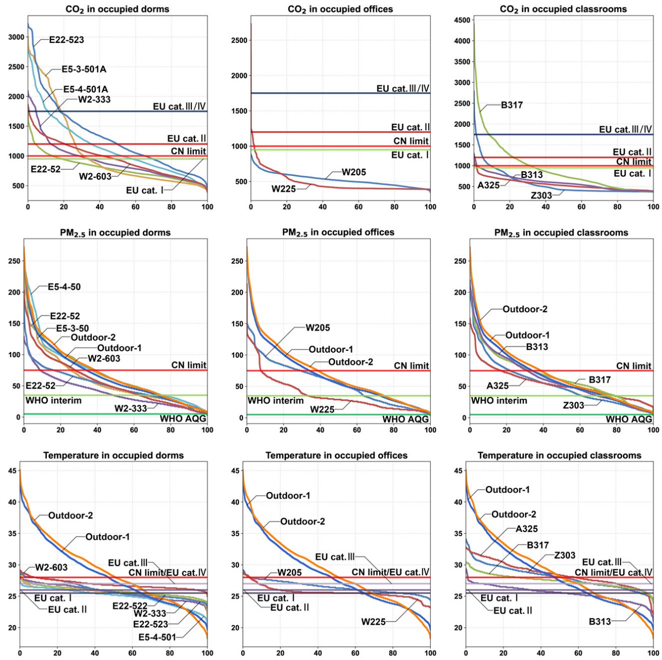

Figure 9. CDJCC Spring semester: duration curves under occupancy, by room.

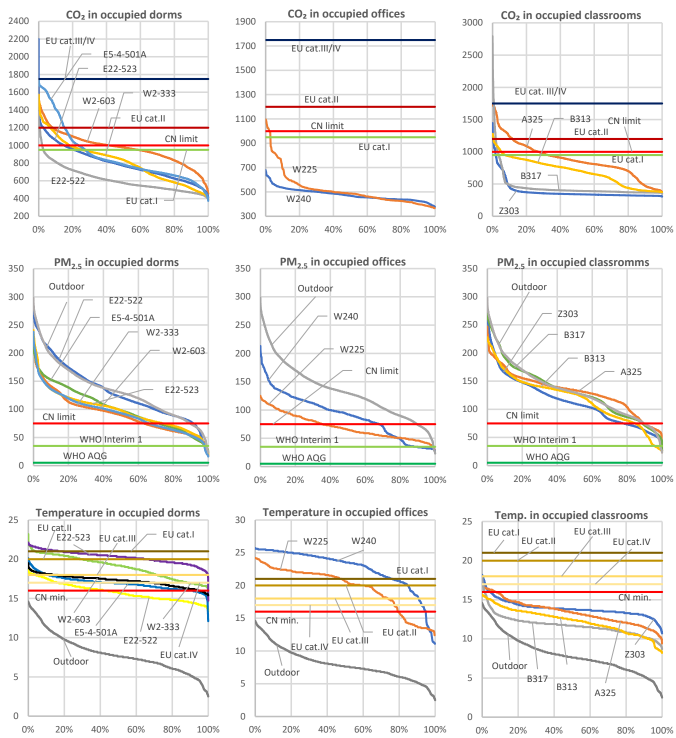

Figure 10. CDJCC Autumn semester: duration curves under occupancy, by room.

Table 6. Occupied-period CO_2, $PM_{2.5}$ and temperature (Med, IQR) with category-compliance labels based on the 5% criterion.

Campus (Semester)	Space Type	CO_2, ppm (Med; IQR; Labels)	$PM_{2.5}$, μg/m^3 (Med; IQR; Labels)	Temperature, °C (Med; IQR; Labels)
CDJCC (Spring)	Dormitory	913; 509; outside of EU cat.III	49; 48; outside of CN limit	26.0; 1.8; CN limit
	Office	489; 160; EU cat.I	41; 50; outside of CN limit	25.9; 1.9; CN limit
	Classroom	552; 352; EU cat.III	52; 46; outside of CN limit	27.2; 2.4; outside of CN limit
	Outdoor	419; 72; N/A	57; 60; outside of CN limit	27.9; 7.4; N/A
TalTech (Spring)	Office	604; 84; EU cat.I	0; 1; WHO AQG	23.9; 2.2; EU cat.I
	Classroom	611; 159; EU cat.III	0; 1; WHO AQG	23.3; 1.8; EU cat.I
	Outdoor	481; 72; N/A	2; 6; WHO Interim 1	11.8; 6.0; N/A
CDJCC (Autumn)	Dormitory	789; 355; EU cat.III	96; 50; outside of CN limit	17.4; 2.8; outside of CN limit
	Office	474; 74; EU cat.I	83; 54.8; outside of CN limit	22.4; 4.1; outside of CN limit
	Classroom	388; 84; CN limit	124; 64; outside of CN limit	12.6; 2.3; outside of CN limit
	Outdoor	359; 52; N/A	130; 63; outside of CN limit	7.6; 2.8; N/A
TalTech (Autumn)	Office	604; 98; EU cat.I	0; 1; WHO AQG	21.8; 1.7; EU cat.III
	Classroom	621; 191; EU cat.III	0; 1; WHO AQG	21.7; 1.7; EU cat.III
	Outdoor	496; 52; N/A	0; 4; WHO Interim 1	4.9; 5.4; N/A

In the autumn semester, the medians for dormitories/offices/classrooms/outdoors were 789/474/388/359 ppm. The recorded outdoor CO_2 concentrations dipping below the 400 ppm baseline is attributed to a combination of the campus's ultra-high vegetation coverage, which may create a localized carbon sink effect, and a potential sensor offset in the lower range. However, for the core objective of assessing indoor IEQ, this anomaly is inconsequential. Any such low-range sensor inaccuracy diminishes non-linearly and becomes negligible at the higher CO_2 concentrations typical of occupied indoor spaces. Therefore, no compensation was applied to the outdoor data, as the indoor assessments remain valid when benchmarked against the unadjusted outdoor readings. The typical indoor CO_2 concentrations (box ranges) for all space types were below the winter limit set by the adopted CN standard (1000 ppm). The median ranking from high to low was dormitories > offices > classrooms. Dormitories had relatively longer box ranges, which indicates larger typical fluctuation. When interpreted in conjunction with the duration curves, the results indicate that, in the autumn semester, CO_2 concentrations in dormitories exhibit larger typical fluctuations with occasional extreme values.

Comparing spring and autumn across space types shows that both the median and the typical CO_2 concentrations (box ranges) were generally lower in the autumn semester than in the spring semester, with the exception that office CO_2 concentration was similar between the two semesters. For offices and classrooms, the box ranges in the autumn semester were shorter than in the spring semester, implying smaller typical fluctuations and the absence of extremely high values in the autumn semester. Dormitories showed similar patterns across the two terms. The overall drop in the autumn semester medians and the marked shortening of office/classroom boxes may reflect the combined effects of greater indoor–outdoor temperature differences (enhancing buoyancy-driven ventilation and infiltration) together with relatively lower outdoor CO_2 concentration, which dilutes extremes and tightens the typical interval. The spring–autumn similarity in offices may result from stable occupancy and operating strategies. Dormitories retained long boxes in the autumn semester, suggesting that differences in residential behavior and nighttime door/window closures persist across seasons, limiting the dampening effect of seasonal change.

- $PM_{2.5}$

In the spring semester (Figures 8–10 and Table 6), the median $PM_{2.5}$ levels for dormitories/offices/classrooms/outdoors were 49/41/52/57 μg/m^3, with the median ranking classroom > dormitory > office. In dormitories, 4% of the typical $PM_{2.5}$ levels (box range) exceeded the summer limit of 75 μg/m^3 specified by the adopted CN standard, whereas the box ranges for all other space types remained below this limit. Across space types, the typical ranges were relatively long; classroom levels were nearly at outdoor levels and tracked outdoor trends, indicating larger typical fluctuations, likely influenced by outdoor $PM_{2.5}$ levels. When interpreted in conjunction with the duration curves, the results indicate that, in the spring semester, $PM_{2.5}$ levels exhibit larger typical fluctuations with periods of extreme values.

In the autumn semester, medians for dormitories/offices/classrooms/outdoors were 96/83/124/130 μg/m^3, ranked classroom > dormitory > office. Typical $PM_{2.5}$ ranges for all space types were above the WHO Interim Target 1 limit (35 μg/m^3), and exceeded the winter limit under the adopted CN standard in 92% of dormitory cases, 62% of office cases, and 100% of classroom cases. Overall, typical ranges were long; classroom values were again close to outdoor levels and mirrored outdoor trends, consistent with the spring pattern.

Comparison between the two semesters shows that both the medians and the typical $PM_{2.5}$ levels (box ranges) were higher in the autumn semester than in the spring semester. In both semesters, the ranking remained classroom > dormitory > office, and classroom values were closest to outdoor levels. Because $PM_{2.5}$ exposure is primarily governed by outdoor infiltration and ventilation rates, the seasonal rise in medians and typical ranges is likely driven by higher outdoor backgrounds and variability rather than changes in indoor sources.

- Temperature

In the spring semester (Figures 8–10 and Table 6), the median temperatures for dormitories/offices/classrooms/outdoors were 26.0/25.9/27.2/27.9 °C, with the median ranking classroom > dormitory > office. Typical temperature ranges for all space types were below the summer upper limit specified by the adopted CN standard (28 °C), except in classrooms, where 17% exceeded the limit; indoor temperatures were generally lower than outdoors. Typical ranges across space types were similar and relatively short in the spring semester except for classrooms. When interpreted in conjunction with the duration curves, the results indicate that, in the spring semester, typical temperature fluctuations were modest and episodes of extreme variation were limited, except in classrooms.

In the autumn semester, the medians for dormitories/offices/classrooms/outdoors were 17.4/22.4/12.6/7.6 °C, ranked office > dormitory > classroom. Typical temperature ranges differed markedly across space types: the office box lay above the winter lower limit set by EU cat. II (20 °C), the dormitory box above the winter lower limit set by the adopted CN standard (16 °C), and the classroom box below the winter lower limit set by the adopted CN standard (16 °C). Overall, typical temperature ranges were relatively short, indicating small typical fluctuations across space types. When interpreted in conjunction with the duration curves, the results indicate that, in the autumn semester, offices exhibited generally stable temperatures, classrooms were overall colder, and both dormitories and classrooms displayed larger temperature extremes.

Comparison between spring and autumn shows that, due to outdoor temperature effects, typical ranges and medians were higher in the spring semester. Relative to spring, the autumn boxes for dormitories and offices were longer. Classrooms showed a much larger overall decrease in temperature relative to spring, with the same pattern as before and the closest alignment with outdoor conditions. This indicates larger typical fluctuations in dormitories and offices in the autumn semester, with dormitories showing larger extremes and offices showing larger low-temperature extremes, while classrooms were more influenced by outdoor temperatures. A plausible explanation is that autumn brings outdoor cooling, intermittent heating, and natural ventilation operating simultaneously, leading to mostly stable but occasionally low temperatures in offices, greater variability in dormitories, and classrooms that are overall colder and more closely track outdoor conditions.

3.2.2. Spring–Autumn Semester Comparisons at TalTech

- CO_2

In the spring semester at TalTech (Figures 8 and 11 and Table 6), the median CO_2 values for offices/classrooms/outdoors were 604/611/481 ppm. There was no clear difference among space types in the medians, and the typical concentration intervals (box ranges) were similar. All space types were below the limit set by EU cat. I (950 ppm); the classroom box was relatively long with a low-positioned median, indicating relatively larger fluctuations within the typical range and occasional extremely high values.

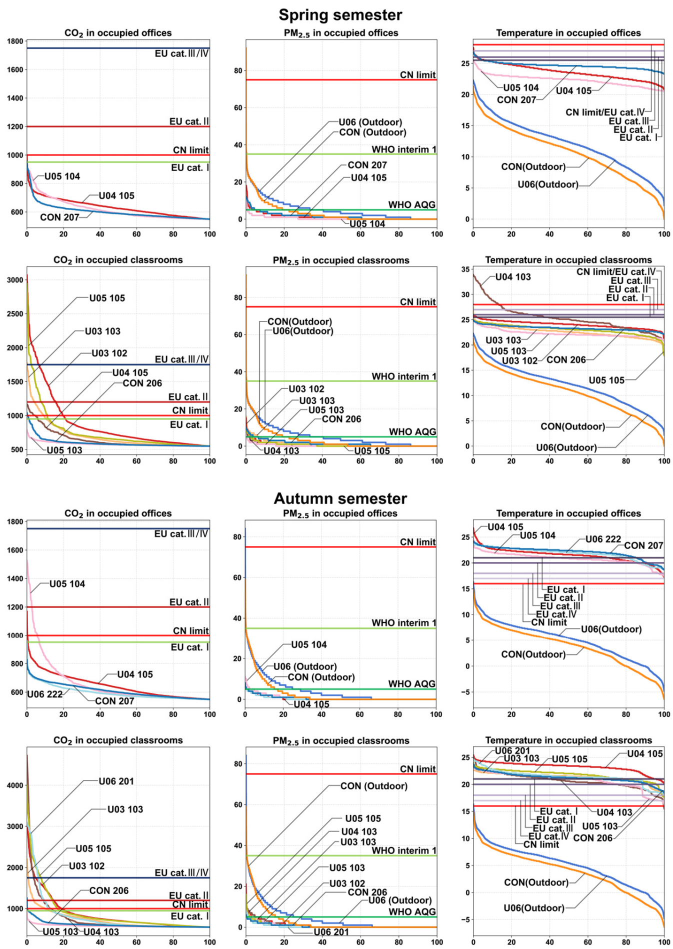

Figure 11. TalTech Spring and Autumn semester: duration curves under occupancy, by room.

In the autumn semester, the medians for offices/classrooms/outdoors were 604/621/496 ppm, again with no clear differences among space types. The typical concentration intervals for all spaces were below the limit set by EU cat. I (950 ppm), with no obvious change from the spring pattern.

Comparing the two semesters, the upper quartiles of the autumn semester boxes were slightly higher than in the spring semester in spite of unchanged ventilation strategies, likely due to weather-driven reduced outdoor activities leading to a higher indoor occupancy.

- $PM_{2.5}$

In the spring semester (Figures 8 and 11 and Table 6), the median $PM_{2.5}$ values for offices/classrooms/outdoors were 0/0/2. There were no obvious differences among spaces, and all typical concentration intervals were below the WHO AQG guideline (5 μg/m^3).

In the autumn semester, the medians for offices/classrooms/outdoors were 0/0/0, with no obvious differences among spaces; all typical concentration intervals were below the WHO AQG guideline (5 μg/m^3).

Comparing spring and autumn, the outdoor typical concentration interval was slightly higher in the spring semester than in the autumn semester, whereas the indoor typical intervals were fairly constant. This suggests that filtration in the mechanical ventilation system keeps indoor pollutant levels consistently low.

- Temperature

In the spring semester (Figures 8 and 11 and Table 6), the median temperatures for offices/classrooms/outdoors were 23.9/23.3/11.8 °C, with no substantial differences among spaces. Typical temperature intervals for all spaces were below the summer upper limit set by EU cat. I (25.5 °C); the typical intervals were similar and relatively short, indicating limited indoor temperature fluctuations within a narrow range.

In the autumn semester, the median temperatures for offices/classrooms/outdoors were 21.8/21.7/4.9 °C, again with no substantial differences among spaces. Typical temperature intervals were mostly above the EU cat. I winter lower limit (21 °C), except in offices, where 20% fell below the EU cat. I winter lower limit (21 °C). Differences among space types were small, indicating limited indoor temperature fluctuations within a narrow range.

Comparing the spring semester and the autumn semester, typical temperature intervals and medians were generally lower in the autumn semester than in the spring semester; outdoors, both the typical interval and the median were lower in the autumn semester, with no obvious change in the overall pattern. The outdoor difference exceeded the indoor difference, highlighting the advantage of mechanical ventilation in maintaining indoor thermal comfort.

3.2.3. Comparative Analysis of CDJCC and TalTech

- CO_2

Comparing the spring semesters at CDJCC and TalTech (Figures 8–12 and Table 6), the outdoor CO_2 typical interval and median at TalTech were slightly higher than at CDJCC, with broadly similar trends. The medians for offices/classrooms at TalTech were slightly higher than at CDJCC. However, CDJCC showed longer typical intervals than TalTech, indicating greater variability within the typical range and more pronounced high-end extremes in offices/classrooms at CDJCC.

Comparing the autumn semesters, TalTech again had a slightly higher outdoor CO_2 typical interval and median than CDJCC, with similar overall trends. The classroom median at TalTech sat lower within its typical interval relative to CDJCC, indicating a tendency toward high-end fluctuations in the autumn semester.

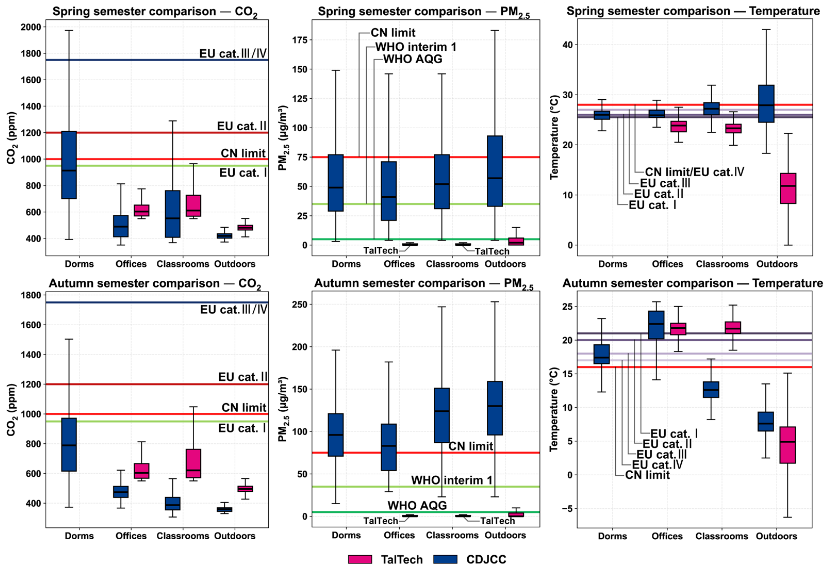

Figure 12. Spring–Autumn IEQ within same room types: CDJCC compared with TalTech.

Given that CDJCC uses mixed-mode ventilation (mostly natural ventilation with supplemental air-conditioning) while TalTech uses mechanical ventilation with district heating, these differences reflect the advantage of mechanical systems in controlling indoor CO_2 concentrations.

- $PM_{2.5}$

In the spring semester (Figures 8–12 and Table 6), the outdoor $PM_{2.5}$ typical interval and median at CDJCC were markedly higher than at TalTech, and indoor spaces at both campuses followed the same trend. At both campuses, indoor typical intervals and medians were lower than outdoors.

In the autumn semester, the pattern was similar to spring. Overall, indoor $PM_{2.5}$ levels were driven primarily by outdoor infiltration; filtration in mechanical ventilation can provide supplementary reduction.

- Temperature

In the spring semester (Figures 8–12 and Table 6), CDJCC's outdoor typical temperature interval and median were significantly higher than TalTech's; office/classroom typical intervals and medians were slightly higher at CDJCC than at TalTech. Space-type-wise temperature trends were broadly similar, but CDJCC showed a tighter coupling between indoor and outdoor temperatures.

In the autumn semester, CDJCC's outdoor typical interval and median were slightly higher, while TalTech's outdoor temperature fluctuated more. CDJCC offices had a slightly higher median but longer typical intervals, indicating greater variability and more low-temperature extremes. CDJCC classrooms had a markedly lower typical interval and median than TalTech, with similar trends, implying a substantially lower overall temperature range in the autumn semester at CDJCC.

Overall, TalTech exhibited more stable indoor temperature control with weaker coupling to outdoor conditions, whereas CDJCC showed weaker stability in offices and classrooms during autumn, larger inter-room differences, and stronger coupling to outdoor temperatures.

4. Discussion and Implications

4.1. Cross-Campus Summary of Empirical IEQ Findings

4.1.1. Climate Zones/Seasons and Ventilation Modes

In cross-climate and cross-ventilation-mode comparisons, this study corroborates three points: (1) under a predominantly natural-ventilation scenario, the climate zone and season primarily determine the baseline values of CO_2 and $PM_{2.5}$ in campus IEQ, whereas temperature can generally be kept thermally comfortable by air-conditioning; (2) the ventilation-system configuration chiefly determines indoor temperature variability—that is, the lengths of the whiskers and box ranges in Figures 8 and 12, as well as the steepness of each room's duration curves in Figures 9–11; and (3) system configuration exerts a stronger influence on IEQ than climate differences alone.

In mechanically ventilated spaces with effective filtration, high-end CO_2 and $PM_{2.5}$ tails shrink, temperature exceedance times drop, and overall IEQ variability decreases. Under natural ventilation without dedicated outdoor-air systems, IEQ outcomes become highly sensitive to window-opening and operational strategies, and in unfavorable seasons CO_2, $PM_{2.5}$ and temperature fluctuate more strongly, highlighting the role of ventilation and filtration in controlling extremes.

Within a given climate zone, season effectively sets the IEQ baseline. Winter typically raises overall CO_2 and particulate levels, and where ventilation is weak or relies on natural ventilation, winter pollution and low temperatures together with summer overheating more readily combine to create indoor extremes.

4.1.2. Space-Type IEQ Risk and Staged Control Strategy

Across space types, poorly adapted airflow organization is the main risk, especially in high-occupancy, high-density rooms. Dormitories and classrooms often have insufficient outdoor-air supply and thus show persistently elevated CO_2 and more extremes, whereas lower-density offices exhibit more moderate IEQ conditions. This indicates that high-occupancy/high-density spaces require stronger outdoor-air provision and more responsive demand-controlled ventilation to reduce the risk of extremes.

Improvement/remedial strategies should use the overall patterns by space type in the box plots for global control and take above/below-threshold durations in the duration curves as core indicators, following the sequence "secure the median first, then control variability." (1) First, improve overall comfort through effective airflow organization and ventilation systems so that the medians and box ranges of over-limit spaces gradually converge toward compliance. (2) At the individual-space level, implement context-specific operational optimization to make box ranges and whiskers converge, thereby reducing the frequency and magnitude of above/below-limit tail exceedances in the duration curves and stabilizing overall comfort and health.

4.2. Conditional Evaluation Workflow

Through a systematic comparative analysis of campus buildings in a temperate climate and a subtropical monsoon climate, this study developed and validated a new conditional evaluation workflow based on two empirical indicators designated as the seasonal ventilation coefficient indicator λ_{season} and the infiltration factor (I/O).

4.2.1. Seasonal Ventilation Effectiveness Coefficient

The seasonal ventilation coefficient indicator λ_{season} characterizes the relative indoor CO_2 concentration under comparable occupancy density between the spring semester and the autumn semester, thereby quantifying the "effective ventilation difference" attributable to season. It is defined as the ratio of the average indoor CO_2 concentration in the autumn semester to that in the spring semester (see Equation (15)).

$$\lambda_{season} = \frac{\overline{CO_2}_{Autumn}}{\overline{CO_2}_{Spring}} \tag{15}$$

in which: λ_{season} is the "seasonal ventilation effectiveness coefficient," representing the relative difference in effective ventilation between the spring semester and the autumn semester under comparable occupancy conditions. $\overline{CO_2}_{Spring}$ denotes the average indoor CO_2 during occupied periods in the spring semester; $\overline{CO_2}_{Autumn}$ denotes the average indoor CO_2 during occupied periods in the autumn semester. Ground-truth occupant counts (and per-room occupancy probabilities) were not available in this campaign; therefore, occupied periods were identified using binary presence flags (CDJCC) and CO_2-based inference (TalTech), and λ_{season} is not normalized on a per capita basis. Mathematically, $\lambda_{season} > 1$ means that indoor CO_2 is higher (and effective ventilation is weaker) in the autumn semester than in the spring semester; conversely, $\lambda_{season} < 1$ indicates lower CO_2 (i.e., stronger effective ventilation) in the autumn semester under comparable occupancy conditions. When computing this coefficient, comparable occupancy density/activity intensity, consistent instrument calibration, and specified averaging method and time window should be ensured as prerequisites.

λ_{season} is used to quantify the change in effective ventilation attributable to seasonal differences: under comparable occupancy density and activity intensity (e.g., identical class schedules/office hours), take the autumn-to-spring ratio of the indoor CO_2 averages over corresponding time spans (preferably the median or mean during occupied periods). Under a well-mixed condition, indoor CO_2 concentration is approximately inversely proportional to the effective air-change rate; therefore, $\lambda_{season} > 1$ indicates weaker effective ventilation in the autumn semester than in the spring semester. To achieve the same indoor CO_2 target in the autumn semester as in the spring semester, the ventilation rate would need to be increased by approximately λ_{season}.

For example, for CDJCC indoor spaces we obtained a campus-level mean λ_{season} = 0.9076 (95% CI: 0.7490–1.0661), indicating a weak tendency toward lower CO_2 (i.e., slightly stronger effective ventilation) in the autumn semester relative to the spring semester under the present monitoring conditions; however, the confidence interval overlaps unity, suggesting that the campus-wide seasonal effect is not robust at the 95% confidence level under the current assumptions.

In this study, the proposed seasonal ventilation coefficient λ_{season} was further examined using the monitoring data from the CDJCC and TalTech campuses. For each monitoring point, daily mean indoor CO_2 concentrations were first computed separately for the spring semester and the autumn semester. All spring-semester daily means were then fully crossed with all autumn-semester daily means within the same point to generate a set of inter-semester CO_2 ratio samples, from which a representative λ_{season} was derived for each room. The resulting room-level λ_{season} values were subsequently grouped by campus and indoor space type (classrooms, dorms/bedrooms, and offices). For each group, the number of rooms, the mean λ_{season}, its standard deviation, and the 95% confidence interval were estimated using a t-distribution–based approach (t critical value multiplied by the standard error of the mean) (Equation (14)). This room-based procedure treats rooms as independent observational units and uses the t-distribution confidence intervals as an empirical consistency check: it demonstrates that, for the present dataset, the observed seasonal ventilation coefficients across different campuses and indoor space types fall within ranges compatible with the conceptual interpretation of λ_{season} given above. The summary statistics of λ_{season} for each group are reported in Table 7.

https://doi.org/10.3390/buildings16020283

Table 7. t-distribution-based 95% confidence interval test results for λ_{season} using the CDJCC and TalTech CO_2 datasets as examples.

Campus	Group	N	Mean	SD	CI95_Low	CI95_High
CDJCC	classrooms	4	0.9822	0.4291	0.2994	1.665
	dorms	6	0.8486	0.1326	0.7094	0.9877
	offices	2	0.9353	0.0039	0.9005	0.9701
	outdoors	2	0.8496	0.0005	0.8447	0.8545
CDJCC	indoor	12	0.9076	0.2495	0.749	1.0661
TalTech	classrooms	6	1.1117	0.1119	0.9943	1.2292
	office	3	1.0221	0.0164	0.9814	1.0628
	outdoors	2	1.0307	0.0042	0.9931	1.0684
TalTech	indoor	9	1.0819	0.0995	1.0053	1.1584

From a comparative perspective, the room-level λ_{season} values in Table 7 reveal clear differences both within and between campuses. At CDJCC, dorms and offices have mean λ_{season} below unity, while classrooms are close to unity; the campus-wide indoor mean is λ_{season} = 0.9076 with a 95% confidence interval of 0.7490–1.0661, indicating a weak overall tendency toward lower CO_2 (i.e., slightly stronger effective ventilation) in the autumn semester, while the confidence interval overlaps unity. Among CDJCC indoor spaces, classrooms exhibit the largest between-room variability, whereas offices show the most clustered room-level coefficients and dorms fall in between, suggesting heterogeneous operational and occupant-driven effects across room types. At TalTech, by contrast, the mean λ_{season} for both classrooms and offices is above unity, and the campus-wide indoor confidence interval lies entirely above 1, implying weaker effective ventilation in the autumn semester than in the spring semester for this dataset. Outdoor λ_{season} behaves differently across the two campuses: it is close to unity at TalTech, whereas it is noticeably below 1 at CDJCC in this dataset, indicating that outdoor background CO_2 seasonality may not be negligible; therefore, indoor λ_{season} should be interpreted in conjunction with outdoor conditions (and, where relevant, the I/O indicator). Overall, these patterns support the intended interpretation of λ_{season} as a room-level indicator of seasonal ventilation differences and illustrate how the proposed coefficient behaves across different room types and campuses.

4.2.2. Infiltration Factor

The infiltration factor (I/O) is derived from paired indoor–outdoor monitoring and is defined as the ratio of the seasonal indoor average $PM_{2.5}$ level to the outdoor average $PM_{2.5}$ level over the same period (see Equation (16)).

$$I/O = \frac{\overline{PM_{2.5}}_{indoor}}{\overline{PM_{2.5}}_{outdoor}} \tag{16}$$

where I/O is the "infiltration factor," measuring the coupling strength between indoor and outdoor; $\overline{PM_{2.5}}_{indoor}$ denotes the synchronized average indoor $PM_{2.5}$ level, and $\overline{PM_{2.5}}_{outdoor}$ the synchronized average outdoor $PM_{2.5}$ level.

An I/O close to 1 indicates high coupling (frequent window opening, weak filtration, strong outdoor penetration); values well below 1 indicate effective filtration/enclosure (substantial attenuation of particles entering indoors); values greater than 1 typically suggest indoor sources (e.g., cooking, printing, cleaning, dust resuspension) or issues with time pairing/instrument drift and should be reviewed. As a practical guide, 0.5–0.8 indicates moderate coupling; 0.8–0.95 indicates high coupling.

Linking to ventilation strategy: when I/O is high and outdoor pollution is high, reduce natural intake and/or strengthen filtration; when indoor $PM_{2.5}$ level is high but outdoor air is clean (e.g., after rain or at dawn), opportunistic ventilation can lower indoor $PM_{2.5}$ level at low cost.

In this study, the room-level $PM_{2.5}$ indoor–outdoor ratio I/O, as defined in the conceptual framework, is further examined using monitoring data from the CDJCC and TalTech campuses. For each monitoring point, continuous $PM_{2.5}$ observations were first aggregated into hourly mean indoor and outdoor concentrations separately for the spring semester and the autumn semester. Within each monitoring point and semester, hourly $PM_{2.5}$ I/O values were then obtained by pairing indoor and outdoor hourly means at the same hour. These semester-specific hourly I/O samples were subsequently aggregated to the room level by taking the arithmetic mean over all valid hours, yielding a room-level $PM_{2.5}$ I/O indicator for each semester.

The resulting room-level I/O values were grouped by campus, semester (spring vs. autumn), and indoor space type (classrooms, dorms and offices). For each group, the number of rooms, the mean room-level I/O, its standard deviation, and the 95% confidence interval were estimated using a t-distribution–based approach (t critical value multiplied by the standard error of the mean) (Equation (14)). Because $PM_{2.5}$ concentrations at TalTech are frequently at or near the sensor's effective resolution, some groups can exhibit near-zero central tendencies; under a t-distribution CI formulation, this may yield a negative lower bound, which should be interpreted as a statistical artifact rather than a physically negative infiltration. In this context, rooms are treated as independent observational units, and the t-distribution confidence intervals are used as an empirical consistency check of the proposed I/O indicator, rather than as the basis for deriving it. The summary statistics for all campus–semester–room-type combinations are reported in Table 8 and should be interpreted as a data-based demonstration of how the $PM_{2.5}$ I/O behaves under real monitoring conditions.

Table 8. t-distribution-based 95% confidence interval test results for I/O using the CDJCC and TalTech $PM_{2.5}$ datasets as examples (CI is reported as computed without truncation; negative lower bounds may occur when values are near zero).

Campus	Season	Group	N	Mean	SD	CI95_Low	CI95_High
CDJCC	spring semester	classrooms	4	1.0543	0.0519	0.9717	1.0951
		dorms	6	0.8737	0.0978	0.7711	0.9798
		offices	2	0.9942	0.032	0.7069	1.0192
		all	12	0.954	0.1124	0.8826	0.9919
	autumn semester	classrooms	4	0.9496	0.0592	0.8554	1.0266
		dorms	6	0.7997	0.091	0.7043	0.7917
		offices	2	0.7743	0.0267	0.5343	1.1910
		all	12	0.8454	0.1039	0.7794	0.8669
	spring and autumn semester		24	0.8997	0.1195	0.8493	0.9502
TalTech	spring semester	classrooms	6	0.3532	0.3869	−0.0528	1.0444
		office	3	0.379	0.3018	−0.3708	2.6886
		all	9	0.3618	0.3413	0.0994	0.9863
	autumn semester	classrooms	7	0.1681	0.0981	0.0774	0.4744
		office	4	0.2244	0.073	0.1082	0.6135
		all	11	0.1886	0.0905	0.1278	0.4034
	spring and autumn semester		20	0.2665	0.2474	0.1508	0.3823

From a comparative perspective, the room-level $PM_{2.5}$ I/O values in Table 8 reveal systematic differences both within and between campuses. At CDJCC, indoor I/O values are generally close to or moderately below unity in the spring semester, and tend to decrease further in the autumn semester, indicating that indoor $PM_{2.5}$ is on average similar to, or somewhat lower than, outdoor levels, with a modest seasonal enhancement of indoor removal or shielding in autumn. Among CDJCC room types, dorms exhibit both lower mean I/O and larger between-room variability than classrooms and offices, consistent with a stronger influence of occupant-controlled window opening and other room-specific behaviors.

At TalTech, by contrast, room-level $PM_{2.5}$ I/O values are substantially below unity in both semesters, and the campus-wide indoor confidence intervals lie well below 1, especially in the autumn semester. We note that ratios involving near-zero indoor $PM_{2.5}$ values can be mathematically sensitive; therefore, TalTech I/O results—especially for groups with very low indoor $PM_{2.5}$—should be read primarily as evidence of strong attenuation rather than as a precise point estimate. This pattern indicates a stronger overall reduction in outdoor $PM_{2.5}$ indoors, reflecting more effective removal, filtration, or infiltration/ventilation characteristics in the TalTech building stock for the present dataset. The relatively wide confidence intervals for some spring-semester groups, particularly where the number of rooms is small, suggest notable between-room variability and the influence of episodic events, but the combined spring–autumn statistics still consistently point to I/O values markedly below 1. Overall, these results illustrate that the $PM_{2.5}$ I/O indicator, as proposed in this study, behaves in a physically meaningful way across campuses, semesters, and room types, and provide an empirical validation of its usefulness for comparing effective particle removal between indoor environments.

5. Conclusions

5.1. IEQ Assessment Decision Process

Upon introduction of the two empirical indicators, the IEQ assessment decision workflow can be summarized using the workflow illustrated in Figure 13.

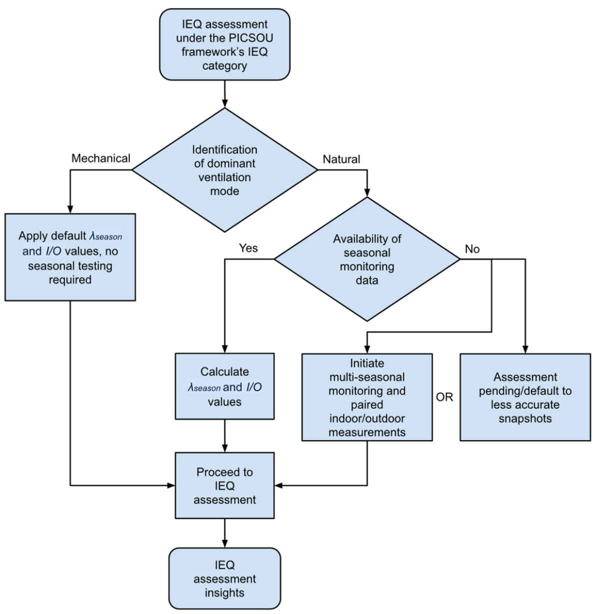

Figure 13. Decision workflow for climate-resilient IEQ assessment under the PICSOU framework.

5.2. Natural Ventilation Strategy Recommendations

For naturally ventilated buildings, our diagnostic workflow yields three pragmatic, actionable measures:

1. User-centered ventilation scheduling. A quantified λ_{season} (e.g., 2.0) provides the evidence base for structured winter ventilation intervals: briefly open windows fully during periods when outdoor $PM_{2.5}$ levels are low (guided by real-time outdoor AQI, e.g., between classes) to quickly dilute accumulated CO_2 concentration while minimizing thermal-comfort loss and particulate matter ingress.
2. Supplemental filtration during low-ventilation periods. Even when outdoor air quality is generally good, a high I/O indicates the need for air purifiers so that, with windows closed in winter, indoor $PM_{2.5}$ levels are decoupled from outdoor pollution—without changing the basic natural-ventilation strategy.
3. Operations tuned to outdoor AQI coupling. For example, when the summer I/O is about 0.95, prioritize ventilation during rainfall or immediately afterward, when outdoor $PM_{2.5}$ levels are naturally lower; window opening then provides the largest net purification benefit.

5.3. Overall Contributions and Implications

This study addresses the common shortcoming in campus sustainability and IEQ work—static "pass/fail" assessments that do not inform operations—by proposing and validating a closed-loop pathway of assessment $\rightarrow$ decision $\rightarrow$ operation. The pathway is comparable across climates, and directly answers operational questions (when to boost airflow or open windows, whether and how much to filter, and how to calibrate winter–summer baselines), thereby turning evaluation into action.

We introduce FMCW radar module into the IEQ sensing stack as a privacy-preserving, low-power, and scalable method for presence/occupancy detection (occupied vs. unoccupied) and space-use monitoring. FMCW markedly improves the timeliness and usability of data while lowering deployment and maintenance burdens. It tightens the assessment–decision link—e.g., triggering airflow increases when occupied and shifting to energy-saving modes when unoccupied—thereby providing a practical sensing foundation for fine-grained operations in naturally ventilated buildings.

We combine box plots (to read cross-space patterns) with duration curves (to quantify exceedance probabilities for CO_2, $PM_{2.5}$, and temperature), enabling nuanced spatial comparisons. We further propose two actionable metrics: λ_{season} to calibrate winter–summer baselines (i.e., how much to scale the ventilation rate) and I/O to guide opportunistic ventilation and filter strength (i.e., indoor–outdoor coupling). Together, these translate static compliance into executable, day-to-day "how-to-optimize" rules.

For naturally ventilated existing buildings, we offer a scalable approach: replace heavy, permanent deployments with low-cost sampling of λ_{season} and I/O, and adopt time-segmented operation that fuses outdoor air quality with time of day (opportunistic window opening, demand-based filtration). Within this framework, the presence signal picked up by the sensor's FMCW radar module acts as a core trigger, strengthening the assessment–decision–operation loop, lowering data and infrastructure thresholds, and making campus-scale closed-loop control feasible.

Compared with TalTech, CDJCC shows longer box-range (typical-interval) spans and—considered with duration curves—greater within-range variability with more pronounced high-end extremes in offices and classrooms. We also identify a structural paradox: mechanically ventilated buildings often possess rich BMS (Building Management Systems) data but require less seasonal validation, whereas naturally ventilated buildings most need empirical, seasonal validation yet lack ready data. This mismatch constrains the scaling of climate-resilient IEQ assessments and highlights the urgency of baseline data collection and lightweight validation systems for naturally ventilated stock.

Overall, this work advances the PICSOU framework's IEQ category from static compliance to a comparable, governable, and transferable decision layer, with real-time occupancy-enabled data collection as a practical catalyst for closed-loop, low-cost, and scalable operations.

6. Limitations and Future Work

6.1. Limitations of Monitoring Design and Data Coverage

This study has several limitations related to monitoring design and data coverage, particularly with respect to monitoring duration, the number of devices, and variation in teaching activities across semesters.

First, the monitoring campaigns were designed around typical spring and autumn teaching semesters at the two campuses, and were conducted over finite periods within each semester rather than as continuous, multi-year observations. The relatively limited monitoring duration means that the datasets are well suited to characterizing representative conditions for the selected weeks, but they do not capture the full range of inter-annual variability or conditions during other parts of the academic year (for example, early spring, late autumn, or summer recess). Short-term episodes such as rare pollution or heat events may also be underrepresented. In addition, the selected monitoring windows did not include holiday breaks or other atypical occupancy periods, so IEQ responses during these special periods could not be explicitly compared or evaluated. While structuring the analysis by semester improves comparability between the two campuses and between spring–autumn terms, the finite duration of each campaign inevitably constrains how far the results can be generalized in time.

Second, the spatial coverage and number of devices are constrained by practical considerations. Only a limited number of sensors could be deployed, and these were distributed across a subset of buildings and space types on each campus, with a focus on typical teaching and office spaces. Within individual buildings, sensor locations were influenced by access, installation feasibility, safety, and maintenance requirements. As a result, some space typologies—such as certain laboratories, shared learning hubs, recreational areas, and support spaces—are underrepresented or not captured, and the monitored rooms may not span the full spectrum from "best-performing" to "worst-performing" IEQ spaces. For derived indicators such as λ_{season} and I/O, additional data-completeness criteria further reduce the number of usable devices, rooms, and days in the robustness analysis, introducing a further level of selection into the underlying samples.

Third, variation in teaching activities and space use across semesters introduces additional uncertainty. Although the monitored periods were selected to represent regular teaching weeks, there remain unavoidable differences between semesters and years in course timetables, classroom allocation, student numbers, and occupancy patterns (e.g., examination weeks, project weeks, or minor timetable changes). These factors influence how intensively rooms are used and how ventilation systems are operated, and thus may partly contribute to differences observed between semesters and between campuses. The present analysis cannot fully disentangle the effects of climate and ventilation configuration from those of changing teaching activities. In addition, building-envelope performance (e.g., airtightness and thermal properties) was not measured or harmonized across buildings/campuses, so its influence cannot be separated from the observed climate- and ventilation-mode effects.

Taken together, these limitations mean that the present results should be viewed as indicative for the studied campuses and their monitored spring and autumn semesters, rather than as an exhaustive characterization of all campus spaces, seasons, and operational conditions. They also motivate future extensions with longer monitoring periods, a larger number of devices and monitored rooms, and more systematic documentation of teaching and occupancy patterns, which would help to further strengthen the robustness and generality of the conclusions.

6.2. Limitations of Occupancy Representation and Cross-Campus Comparability

A further limitation of this study lies in the different ways in which occupancy is represented at the two campuses. As discussed in Section 3.1, these differences have been examined empirically; here, they are summarized as constraints on the occupancy information used in the analysis.

At CDJCC, all custom-built IEQ sensor units are integrated with an FMCW radar module, and the present study uses radar-based presence as the occupancy signal. This provides a direct, privacy-preserving indication of whether a room is occupied, and forms the basis for linking occupancy to IEQ patterns and for illustrating the assessment–decision–operation loop. At TalTech, by contrast, no dedicated occupancy sensor was available, and occupancy had to be inferred solely from CO_2 time-series patterns. The two campuses therefore differ not only in sensing hardware but also in how "human presence" enters the analysis: one site uses a direct signal, the other relies on an indirect proxy.

The CO_2-based occupancy proxy at TalTech is inherently less specific than radar-based detection. CO_2 dynamics reflect the combined influence of human emissions and air exchange, so elevated or declining concentrations cannot be uniquely attributed to changes in occupancy. Section 3.1 uses CDJCC data as a reference to compare FMCW-derived occupancy with CO_2-based inference, and shows that systematic deviations can occur in certain periods and space types. These findings indicate that a simplified CO_2-only method may misclassify some occupied and unoccupied intervals, and that such biases are difficult to quantify or correct at TalTech, where no independent ground truth is available.

Taken together, these factors mean that the occupancy information used in this study should be regarded as uneven in strength across the two campuses: CDJCC benefits from direct radar-based presence detection, whereas TalTech relies on a CO_2-driven proxy. Although Section 3.1 demonstrates that the two approaches are broadly comparable for the purposes of this study, the remaining discrepancies highlight a limitation in cross-campus comparisons that condition on occupancy, and motivate future work toward more consistent, privacy-preserving occupancy sensing and integrated use of CO_2 and direct presence signals.

6.3. Future Directions for PICSOU's IEQ Category

Based on this study, the PICSOU framework's IEQ module will continue to develop along three main directions.

To keep PICSOU's IEQ category aligned with the evolving EU technical guidance and practice, future updates can formalize a clearly defined indicator set that reflects both health relevance and operational measurability. At minimum, this would include thermal conditions (e.g., operative/air temperature), humidity (RH), ventilation adequacy (e.g., CO_2 and/or ventilation-rate proxies), and key exposure-related pollutants (e.g., $PM_{2.5}$; with VOCs where feasible), while allowing optional extensions for acoustics and lighting when instrumentation is available. Methodologically, adopting an exceedance-based, time-fraction interpretation (as exemplified by TAIL) would allow PICSOU to translate monitoring time series into concise category-level compliance statements, improving robustness across climates and space types [58].

First, the indicator set within the CO_2/$PM_{2.5}$/temperature triad will be expanded and better weighted against learning- and health-relevant outcomes. Additional IEQ dimensions (e.g., humidity, noise, or lighting) can be incorporated in a modular way, allowing the IEQ module to evolve from a minimal, three-indicator set toward a broader, but still interpretable, indicator system that reflects both regulatory limits and outcome-oriented priorities.

Second, the IEQ module will move from largely static interpretations toward more dynamic evaluation, explicitly treating indoor air as a time-varying system rather than as a collection of averages. Building on the duration-curve and box-plot approach used in this study, future work will place greater emphasis on temporal patterns—such as the timing, frequency, and persistence of exceedances—and on how these patterns coincide with occupancy and operation. This opens the door to a tighter coupling between PICSOU's IEQ category, occupancy sensing (e.g., FMCW radar–based presence signals), and operational data, so that the framework can support near-real-time feedback, event detection (e.g., persistent under-ventilation), and rule-based or data-driven control strategies.

Third, PICSOU's IEQ category will be strengthened in terms of cross-climate and cross-space robustness. The present λ_{season} and I/O indicators provide an initial step toward comparable baselines and "how-much-to-adjust" rules across seasons and ventilation modes; future work will extend these concepts by building parameter libraries and baseline ranges across multiple climate zones, campus types, and space categories (e.g., classrooms, dormitories, offices, laboratories). As more campuses and building types are monitored, these libraries can be iteratively refined into a generalizable evaluation system that allows both within-campus benchmarking and cross-campus comparison, while acknowledging local operational constraints.

Overall, these developments aim to advance PICSOU's IEQ category from a compact, proof-of-concept implementation to a more complete, results-oriented and transferable decision-making workflow, one that is capable of integrating more nuanced occupancy information, supporting dynamic operation, while remaining scalable for campus-wide deployment.

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