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Systematic framework for quantitative assessment of Indoor Air Quality under future climate scenarios; 2100s Projection of a Belgian case study

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ABSTRACT

Alteration of Indoor Air Quality (IAQ) levels in the context of changing climate is correlated with shifting air pollutant emissions, variations in ambient climate, and the mitigation/adaptation strategies applied in buildings to deal with increasing extreme weather events and energy demands. In this study, firstly, a systematic modeling-based framework for the quantitative assessment of the impacts of future building retrofit and climate scenarios on IAQ is presented. After describing the framework, its practical implementation in a demonstrative case study is presented. The proposed framework includes three main parts: i) IAQ measurements, ii) IAQ model design, and iii) future IAQ state evaluation. Regarding the case study, fabricated indoor monitoring devices (O_3, CO, NO, NO_2, $PM_{2.5}$, PM_{10}, VOCs, air temperature, relative humidity, and air pressure) based on Low-Cost Sensors were developed, and calibrated with reference analyzers. An indoor measurement campaign was conducted in a naturally ventilated residential building (+2 exhaust fans) in the Wallonia region, south of Belgium (summer of 2021). An IAQ model was designed in the multizone IAQ and ventilation software, CONTAM. The validation and calibration processes were carried out with the aid of experimental data from the indoor measurement campaign. The calibrated IAQ model showed a total conformity of +95 % from the average concentration perspective. Finally, predicted future outdoor air pollution and indoor and outdoor climate data of the case study were fed to the IAQ model (basis-year 2021), and indoor contaminant levels under different climate scenarios were quantitatively assessed till 2100.

1. Introduction

In general, the level of chemical and airborne contaminants in buildings are mainly linked to ventilation characteristics (Air

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Exchange Rate (AER) of outdoor air into indoor), infiltration rates of outdoor air, and indoor emission/sink sources [1,2]. Internal emission/sink sources are linked to occupants' behavior (transient & intermittent), and building elements (permanent). Also, household activities affect the indoor air pollutant removal rate by deposition, filtration, and exfiltration, while some re-suspensions may take place [3]. Indoor emission sources include transient emissions from internal sources (i.e., construction materials, building equipment, and utilities), and intermittent emissions (i.e., burning fuel and candles, smoking, cooking, heating, and occupant behaviors) [3,4]. Indoor air pollutants comprise a wide variety of physical, biological, and chemical contaminants, including but not limited to Carbon Monoxide (CO), Carbon Dioxide (CO_2), Volatile Organic Compounds (VOCs), Nitrogen Oxides (NO & NO_2), Particulate Matter (PM), and Ozone (O_3) [5]. Notably, CO_2 is not cataloged among the selected indoor pollutants by the World Health Organization (WHO), but it has been widely used as an indicator of adequate air ventilation where high indoor CO_2 levels indicate low AERs. High CO_2 levels show poor AERs and potential accumulation of indoor pollutants [6–8].

Future scenarios correlated with the indoor built environment include future climatological scenarios, future Greenhouse gas (GHG) emissions, and future buildings' adaptation and mitigation strategies regarding energy retrofit plans. It is known that these scenarios will impact the contaminant concentrations in residential buildings [2,9–11]. The abovementioned elements can also affect the indoor environment through heat and mass transfers between the interior spaces and the surrounding environment.

To meet the European 2050 climate-neutral targets, current policies suggest present premises must go through extensive retrofitting by utilizing sufficient insulation, high-performance Heating, Ventilation, and Air Conditioning (HVAC) systems, and enhanced air tightness [3,12]. Such measures to air tightness and HVAC systems along with climate change itself, are projected to result in alterations of Indoor Air Quality (IAQ) and personal exposure to airborne contaminants. However, IAQ directly affects public health and well-being [13]. Correspondingly, to mitigate heat waves and peak pollution events residential building models need to consider changing ambient environments [14].

The modeling of IAQ has remained a fundamental subject within the scope of indoor air science for a long time. Well-developed representative IAQ models can be more affordable methods to provide a general insight into the indoor pollutant levels and occupant exposures, rather than time- and cost-consuming large-scale field measurements of indoor air pollution. Several underlying processes and elements in assessing IAQ outcome have been found in previous attempts to create physical and chemical IAQ models, including emissions, infiltration/exfiltration and ventilation, chemical reactions, and surface interactions (sorption and deposition) [15].

The recent literature provides valuable information on the various phenomena associated with future climatological scenarios and their potential impacts on IAQ. Nevertheless, it remains complex and diverse to obtain a quantitative approach for the assessment of interlinked and contradictory impacts of these future scenarios on indoor pollutant concentrations [16,17]. The possible effects on IAQ are frequently ignored in discussions about building energy efficiency. Also, the adequate IAQ level is seen in contrast with efficient energy performance. Moreover, energy-saving measures taken at the expense of IAQ reduction, increase the potential negative risks to occupants' productivity, comfort, and health. Hence, it is imperative to standardize the perception of climate change effects on IAQ by establishing the regulations and policies to be enforced in the building codes and retrofit mandates.

The first two questions considered in evaluating the scientific literature are: "Which studies have quantitatively assessed the impacts of climate change on IAQ?", and "Is there any framework developed to address the climate change effects on IAQ?". Addressing these initial questions, related studies are outlined in the following to the best of the author's knowledge.

Taylor and colleagues employed EnergyPlus 8.0 integrated generic contaminant model to examine the indoor levels of $PM_{2.5}$ under various UK Climate Projections 2009 (UKCP09) scenarios in the London housing stock [18]. Their model takes into account the natural ventilation, infiltration of ambient outdoor $PM_{2.5}$ into indoors, $PM_{2.5}$ produced indoors through fixed trends of cooking and smoking, and reduced building permeabilities. The model doesn't consider any variations in outdoor air PM levels and assumes it is fixed at the level of 13 μg/m^3. The predictions till 2050 indicated that flats have 0.7–0.8 times as much outdoor $PM_{2.5}$ infiltrating indoors compared to detached dwellings, but 1.8–2.8 times higher $PM_{2.5}$ from indoor sources.

Ilacqua and colleagues employed a steady-state single-zone mass balance model to estimate the climate change effects on future indoor air pollution "exposures", in terms of changing infiltration rates [19]. Their model only takes into account the infiltration ratio of pollutants from ambient to indoors through the building leakages, and its correlation with future climate (temperature) scenarios. The model doesn't consider any ventilation type, occupant behavior, and variations in outdoor air pollution levels. The AER via infiltration was estimated by the Lawrence Berkeley National Laboratory (LBL) model [20]. The findings for a temporal range of 2040–2070 indicated a 5 % decrease in infiltration rates would lead to a 2–23 % relative rise in the level of indoor-originating contaminants, along with a 2–18 % decrease in the level of outdoor-originating contaminants.

Chang and colleagues investigated the influence of climate change on the variations of indoor Formaldehyde (HCHO) levels, by the IIAQ-CC model (a developed dynamic multimedia model based on mass balance equations) [21]. The modeling was performed for the temporal range of 2010–2100. The outdoor concentration of HCHO was estimated by a model named KPOP-CC, which allocates meteorological data with IIAQ-CC. However, no available English language reference describing the KPOP-CC model was found. Future indoor HCHO levels were predicted by considering different scenarios of HCHO emission and window openings.

Salthammer and colleagues employed single-zone mass balance and one-dimensional heat transfer models to evaluate the impacts of climate change on PM levels and indoor climate, in a single-family house [22]. The model didn't take into account the impacts of the building envelopes, airflow patterns, indoor emission sources, and mechanical ventilation systems. Also, they only made rough theoretical estimates of future outdoor PM levels based on past data statistics. For warm seasons until 2040, their model estimated a reduction of indoor $PM_{2.5}$ and PM_{10} concentrations by 22 % and 34 %, respectively.

Fazli and colleagues developed national residential energy and indoor air model, to predict energy use and IAQ, in the U.S. dwellings in the mid-21st century [2]. They developed a comprehensive single-zone mass balance model to estimate indoor pollutant concentrations. Their model takes into account infiltration, natural and mechanical ventilation, deposition, reaction, and pollutant removal by HVAC filters. They utilized the CMAQ model to estimate future outdoor air pollution. They considered a series of assumptions for future building characteristics (increased airtightness, implementation of electric stoves and HVAC systems), and population evolution (increased construction in building housing stock and population displacement), while other less predictable parameters were kept constant. Their results showed that indoor levels of PM_1, $PM_{2.5}$, and NO_2 would decrease due to reductions in both indoor and outdoor sources. Also, the indoor levels of O_3 stemming from outdoor origins would rise, potentially increasing indoor chemistry reactions.

Regarding the available frameworks related to IAQ and climate change, we found two relevant studies which are discussed in the following [23,24].

Al Assaad and colleagues proposed a quantitative assessment framework of the IAQ resilience performance of buildings against excessive indoor and outdoor pollution risks [24]. However, their study considers the excessive pollution levels in terms of extreme events without considering climatological scenarios (e.g., sudden system failures, smog, wildfires, extra occupants, and traffic jams). It is noteworthy to mention that in an initial endeavor to simulate IAQ within the context of changing climate, extreme events are not prioritized as their predictions remain a challenge to date [17].

Salthammer and colleagues proposed the Indoor Air Quality Climate Change (IAQCC) model, as a holistic framework for estimating the influence of climate change on IAQ [23]. Their framework includes five sub-models (building physics, emission, chemical-physical, mold growth, and exposure) to simulate indoor climate and air quality as functions of building parameters, residential activities, and ambient conditions. Their framework targets both gas and particulate phases. They presented a case study example of indoor chemistry "limonene/O_3/OH" for a 50 m^3 room. However, similar to their previous study [22], no experimental validation was carried out for O_3, and obtaining future outdoor air pollution was not addressed.

The third question considered in evaluating the scientific literature is: "Do literature studies allow for a universal and comprehensive evaluation of the quantitative assessment of climate change impacts on IAQ?". Addressing the third question, seven criteria are established for a systematic analysis as follows:

1. "IAQ model" represents the type of IAQ model used or developed.
2. "Ventilation type" represents the type of studied ventilation systems.
3 "Future Climate Scenario" represents the driving climatological scenario.
4. "Future air pollution" represents the approach to obtaining future outdoor air pollution concentrations.
5. "Future building characteristics" represent whether the future building airflow characteristics are considered or not.
6. "Future occupant activities" represent whether the future scenarios for variation in occupant activity patterns are considered or not.
7. "Pollutants" representing the addressed contaminants.

The outcomes of the literature analysis, are presented in Table 1. So far, there is a lack of a comprehensive approach to investigate the impacts of climate change on IAQ, quantitatively. To answer our main research question: "How to investigate the IAQ in the context of changing climate quantitatively?", an integral (summative) framework is developed. After describing the framework, its practical implementation is presented through a demonstrative case study (Supplementary file).

In the demonstrative case study (see supplementary file), the development of a long-term baseline IAQ model with experimental validation and calibration was studied. Moreover, empirical validation of IAQ models has not been addressed for more than 7 days in the literature, to the best of the author's knowledge. To cover this gap, the presented case study aims to perform the validation based on the corresponding actual measurements in the summer season (validation of "*73-day*" model performance, for the first time).

The current paper is organized as follows. In Section 2, the methodology including the framework is described. Section 3 presents the results, and discusses the key findings, recommendations, strengths, and limitations. Section 4 concludes the paper.

2. Methodology

Fig. 1 presents the research methodology of the present paper in two main sections. The first section introduces an overall view of the systematic framework. The designed framework is based on a comprehensive study of available resources in the literature, to date [2,17,19,21,23,25]. The second section demonstrates the case study of the present research, which was carried out according to the

Table 1
Studies in the literature quantitively assessed the IAQ under future Climate Change (CC) scenarios.

IAQ-CC Quantitative Studies	IAQ model	Ventilation type	Future Climate Scenario	Future air pollution	Future building characteristics	Future Occupant activities	Target Pollutants
[18]	EnergyPlus	natural	UKCP09	–	✓	✓	$PM_{2.5}$
[19]	single-zone mass balance	–	IPCC A2	–	–	–	Radon, PM_1, $PM_{2.5}$, O_3, Carbonyl, NO_2, HNO_3
[21]	mass balance	natural + mechanical	IPCC RCP8	KPOP-CC	✓	✓	HCHO
[22]	single-zone mass balance	–	IPCC RCP8	–	–	–	$PM_{2.5}$, PM_{10}
[2]	single-zone mass balance	natural + mechanical	IPCC RCP8	CMAQ	✓	–	PM_1, $PM_{2.5}$, NO_2, O_3, VOC, Aldehyde

proposed framework.

2.1. Systematic framework for quantitative assessment of IAQ under future scenarios

The detailed systematic framework comprises three main parts: i) IAQ measurement, ii) IAQ model design, and iii) future IAQ state evaluation, which is presented in Fig. 2 and will be discussed in detail in the current section.

Fundamentally, there exist two methods to measure and quantify the air quality in the built environments: direct and indirect [15]. Direct or *in-situ*, methods require the utility of air quality measuring instruments, either by stationary analyzers (on-site deployment for continuous monitoring, or laboratory application by intermittent sampling) or by LCSs. If resourced correctly, direct approaches can determine indoor pollutant concentrations and personal exposures with acceptable accuracy considering the recognized constraints of the instrument and measurement capabilities. While they might require a significant investment of time and potential expenses, direct techniques can yield precise IAQ measurements for actual pollutants and their concentrations (including extreme cases) along with insights into pollutant sources and emission rates.

Conversely, indirect, methods employ computational modeling and statistical techniques to estimate concentrations of indoor contaminants and individual exposures. A major advantage of employing indirect methods is the ability to use computational IAQ models to assess the potential impacts of large-scale interventions aimed at enhancing the quality of the indoor environment. Nonetheless, the extent of simplification in the spatial-temporal dynamics of physical-chemical processes involving indoor contaminants may vary based on the chosen approaches.

The primary objective of the proposed framework is to offer a systematic solution for quantitative IAQ investigation across the board. Indoor experiments are considered as an essential integral part of the framework, regardless of direct or indirect approaches. This is because even the resilience and accuracy of computational IAQ models can be evaluated and improved using field measurements.

2.1.1. Step 1: IAQ measurements

IAQ is commonly influenced by prevalent air pollutants such as O_3, CO, CO_2, SO_2, NO, NO_2, $PM_{2.5}$, PM_{10}, and VOCs. Alongside typical airborne contaminants, T (air temperature) and Relative Humidity (RH) play a substantial role in influencing IAQ [26,27]. Although advanced measuring/analysis instruments (reference analyzers) allow the exact determination of indoor contaminant concentrations with the highest accuracy and precision, their cost and complicated operations make them unsuitable for various tasks. The main technologies of reference analyzers include but not limited to Gas Chromatography (GC), High-Performance Liquid Chromatography (HPLC), ion chromatography, Mass Spectrometry (MS), Fourier-transform infrared spectroscopy (FTIR), LED-based UV photometric detection, Flame Ionization Detection (FID), Non-Dispersive Infrared Gas detection (NDIR), Chemiluminescence Detection (CLD), Thermal Conductivity Detector (TCD), Electron Capture Detector (ECD), Cavity Attenuated Phase Shift spectroscopy (CAPS), UV fluorescence detection, and paramagnetic ionization detectors [28,29].

The evolution of LCSs has enabled real-time spatial-temporal mapping of the IAQ in indoor environments. Developing sensing networks based on individual sensors needs knowledge of different research fields, which aim to make IAQ an advanced feature of smart homes [30–32].

The measurement accuracy of LCSs is highly correlated with factors such as Air Temperature and RH fluctuations, cross-sensitivity,

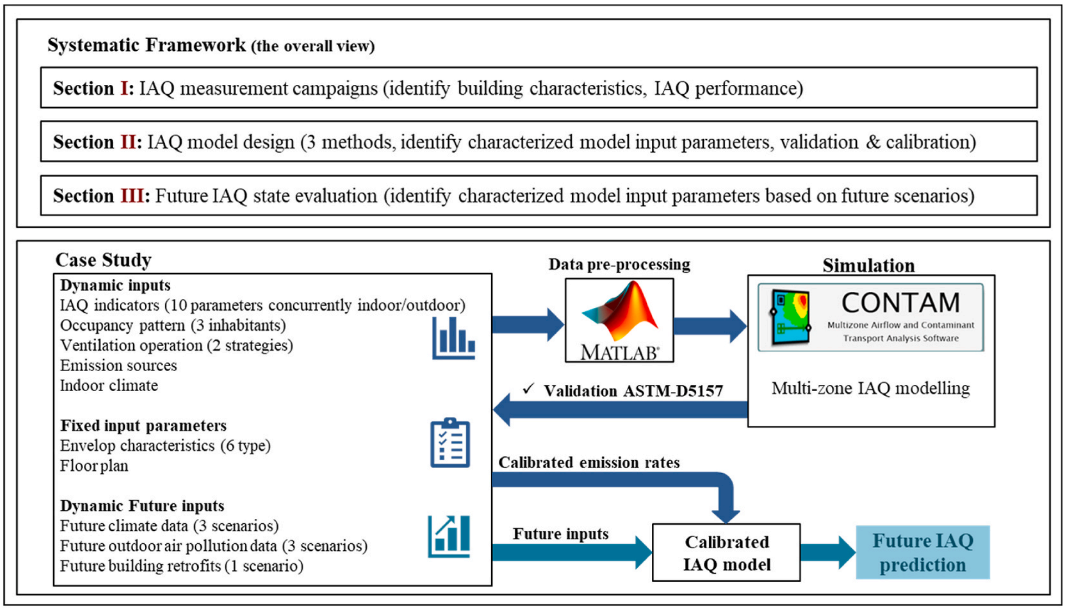

Fig. 1. Study conceptual framework (SCF).

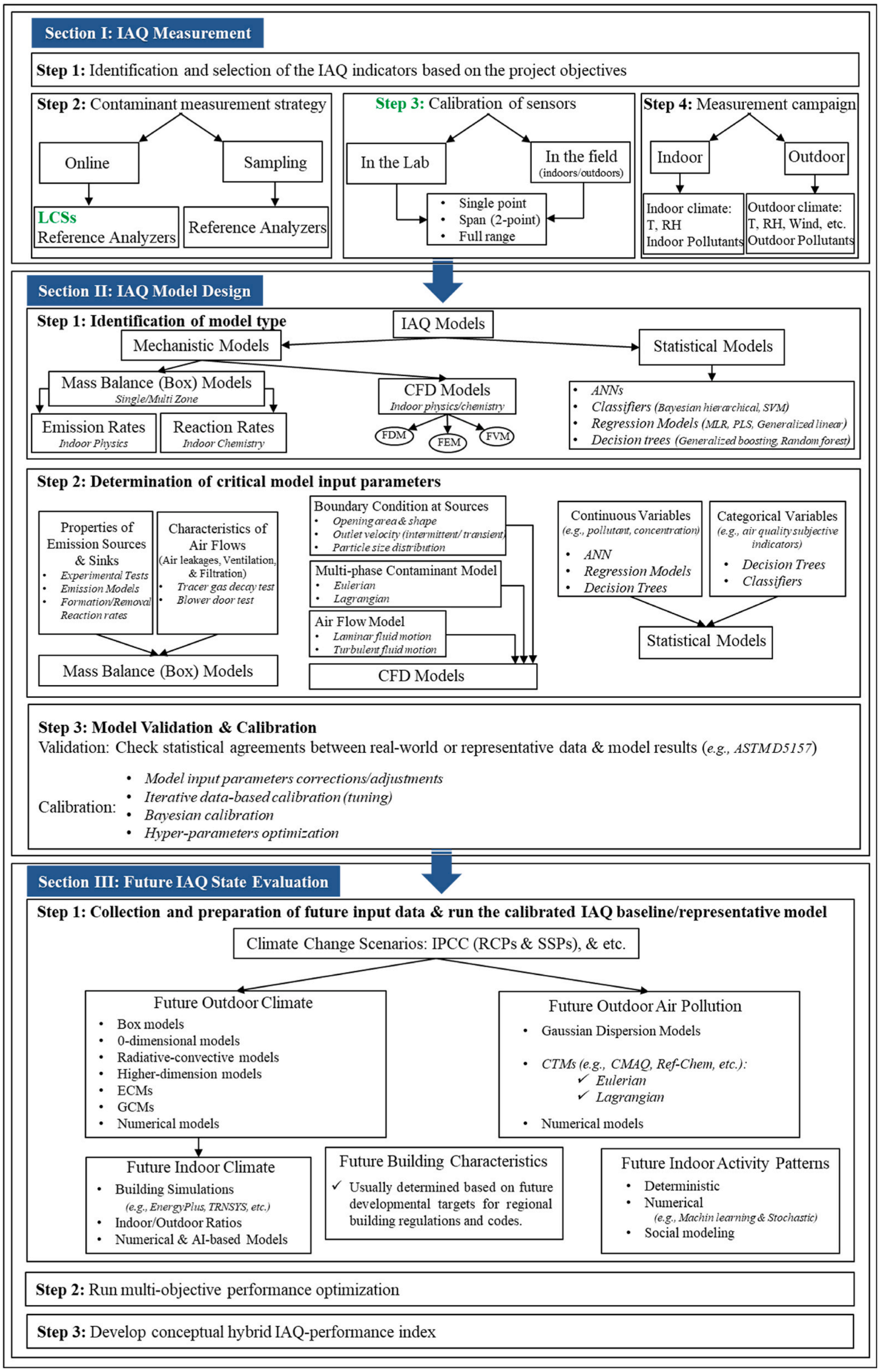

Fig. 2. The systematic framework for quantitative assessment of IAQ under future climate scenarios.

interferences from other compounds, and electronic component tolerances [33,34]. In this regard, uncertainties may stem from sensor calibration and synchronization errors. Uncertainties can also be among sensor data description and sampling, co-location experiments, sensor placement, aerosol concentration determination, and result interpretation [34].

Considering the various approaches available for sensor calibration (e.g., single point, span (2-point), full range), the procedure that is carried out in the presence of reference analyzers in an experimental field is the most accurate one. To obtain the "true" concentrations reported by the LCSs, calibration equations must be derived. Applying RH correction, regression models, and machine learning techniques are the three conventional methods to obtain calibration equations [35,36]. One or more LCSs are often co-located with reference monitors for a short or extended length of time to develop calibration calculations. The associations between the raw output of LCSs and measurements from the reference analyzers are then characterized by a calibration equation [37,38].

Addressing the last step of this part of the framework, the indoor measurement campaigns can be carried out with the support of calibrated sensors or reference analyzers. Generally, the indoor measurement protocols are defined based on the aims, objectives, and exclusive methodology of each research project. The measurement protocol defines various elements including but not limited to measurement duration, measurement locations, number of sensors, sensor positioning, and time interval of data recordings, etc.

2.1.2. Step 2: IAQ model design

IAQ models establish a path to link data of sources, sinks, building elements, and ambient to predict indoor pollutant levels. Various models have been advanced for IAQ applications [39–42]. The choice of model depends on the aimed objectives. The prime applications of IAQ models are:

- Predicting occupant exposures to different indoor contaminants
- Evaluating the influence of specific sources on pollutant levels
- Assessing the effect of particular sources and IAQ control strategies on personal exposure

The intended application of an IAQ model shapes its inherent characteristics and composition. Considering the diverse applications of IAQ models and the range of methodologies employed in their development they can be categorized into three main groups:

1. Mass balance models (Mechanistic approach: indoor physics & chemistry)
2. Computational Fluid Dynamic models (CFD) (Mechanistic approach: indoor physics & chemistry)
3. Statistical models (Numerical approach)

Each general model type, their associated design elements, and corresponding validation and calibration approaches are explained in the supplementary file (see Section S2).

2.1.3. Future IAQ state

To quantitatively evaluate the IAQ in its future state, all or main influential elements must be acquired/determined within the predefined scenarios. This is vital to assemble a comprehensive, and future-representative input dataset for the designated IAQ model. In this regard, the following five questions should be addressed:

1. How would outdoor climate patterns vary in future scenarios?
2. How would outdoor air pollution levels evolve in future scenarios?
3. How would indoor climate, change in the future scenarios?
4. How may building characteristics and retrofit plans advance in future scenarios to address mitigation and adaptation plans?
5. How may human behavior evolve in the context of changing climate?

In the following, it has been tried to study the available solutions and answers related to each question, respectively.

2.1.3.1. Future climate (meteorology). Numerical climate models utilize quantitative techniques to replicate the complicated interactions among pivotal climate drivers (i.e., atmosphere, oceans, land surface, and ice). These models are being employed across a spectrum, ranging from probing the dynamics of the climate system to projecting future climatic scenarios. Not being limited to exclusively numerical formation, climate models can also assume qualitative frameworks and narratives that mainly involve descriptive scenarios for potential futures [43,44].

Climate models can be classified into the following seven main categories:

- Box models
- Zero-dimensional models
- Radiative-convective models
- Higher-dimension models
- Earth System Models (ECMs)
- Global Climate Models or General Circulation Models (GCMs)
- Numerical models (AI-based models)

While simpler models have also been used to provide globally- or regionally-averaged estimates of the climate response, only GCMs are introduced in this section, as a result of their superior capabilities [45].

GCMs demonstrating physical processes in the environment, are the most advanced tools available today for analyzing the reaction of the climate system to the increasing levels of greenhouse gases. Only GCMs in combination with nested grid regional models have the potential to provide geographically and physically consistent estimates. GCMs characterize the climate by a global 3D grid, usually with a horizontal resolution of 250–600 km, and 10–20 vertical layers in the atmosphere [46].

Furthermore, numerous physical phenomena, including those linked with clouds take place on smaller magnitudes and are challenging to be accurately simulated (source of uncertainty). Instead, their recognized attributes need to be averaged across broader scales, within a method referred to as parametrization [47]. Additional uncertainties are caused by the different responses to the same forcing and representation of diverse feedback mechanisms. Distinct responses to the same forcing are caused by the variances in how particular processes and feedback loops are defined. On the other hand, diverse feedback mechanisms include water vapor, temperature rise, clouds and radiation, future atmospheric composition, etc. [48,49].

Intergovernmental Panel on Climate Change (IPCC) is an internationally accredited organization on climate change and is well-known due to carrying a leading role in climate scientists, as well as governments. The panel gathers objective and inclusive scientific data on anthropogenic climate variations. In 2014, the IPCC fifth Assessment Report (AR5) presented four scenarios entitled, Representative Concentration Pathways (RCPs). RCPs were GHG concentration trajectories (not emissions) approved by the IPCC [50]. In 2019, the IPCC AR6 presented five climate scenarios entitled, Shared Socioeconomic Pathways (SSPs) which are scenarios of projected socioeconomic worldwide variations till 2100. These five central states, namely SSP1-1.9, SSP1.-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, represent increasing temperature till 2100. They are employed to originate GHG emissions scenarios by various climate policies [51,52].

The likelihoods of these scenarios were not assessed in the AR5. However, a study from 2020 characterized the SSP5-8.5 as "highly unlikely", SSP3-7.0 as "unlikely", and SSP2-4.5 as "likely" [53]. On the other hand, a report referring to the aforementioned reference; described that the RCP8.5 scenario is most closely with cumulative emissions from 2005 to 2020 [54].

2.1.3.2. Future air pollution. Climate change can impact air contaminant levels by influencing weather, anthropogenic emissions (e.g., attuning responses concerning raised fuel combustion), biogenic emissions, and altering the distribution and characterization of airborne allergens. The local climate impacts atmospheric chemical reactions and the interactions that take place among micro-scale and global-scale environments. By assuming variations of the climate via higher temperatures, air quality is going to be potentially influenced. Yet, the particular magnitude of change (including micro, meso, synoptic, and global), the tendency of alterations in a specific location, and the intensity of variations in air quality remain points of concern. Fig. 3 presents the general assumptions concerning climate change and its attributions to the atmospheric contaminant levels. Taking into account the uncertainties of the general scheme and its elements, it is beneficial to aim at climate change and air pollution simultaneously [55].

Air quality models use mathematical and numerical techniques to simulate the physical and chemical processes that affect air pollutants as they disperse and react in the atmosphere. Fig. 4 presents a general hierarchy of data flow to obtain an air quality model.

Atmospheric dispersion models apply mathematical frameworks to estimate the transfer and dissemination of pollutants within the atmosphere. They find utility in examining an array of pollutants and are frequently deployed to examine the outcomes of emissions from industrial origins or to evaluate potential exposure associated with hazardous substances. General categories of atmospheric dispersion models include [56,57]:

- Gaussian dispersion models
- Chemical Transport Models (CTMs) (Lagrangian & Eulerian)
- Numerical models

Gaussian dispersion models operate on the assumption that the pollutant concentration at any given point is established on factors such as emission rate, meteorological conditions, and distance from the source. They are usually employed due to their relatively straightforward implementation and their ability to estimate concentrations across a broad range of distances from the source [58].

Lagrangian models are defined as the generation and transport of parcels of air "*puffs*" over time. These models trace the transport of pollutants by following a collection of particles representing the pollutants as they move through the atmosphere. They excel in scrutinizing pollutant dispersion over limited distances and in assessing the influence of complex terrain on pollutant transfer [59].

Eulerian models are defined as "*grids* or *boxes*" within which fluxes take place, alongside the chemical production/loss and deposition over time. They utilize a fixed cell system to monitor the transport of pollutants throughout the atmosphere. They prove particularly valuable for examining the distant (long-range) movement of pollutants and for evaluating the effects of emissions by

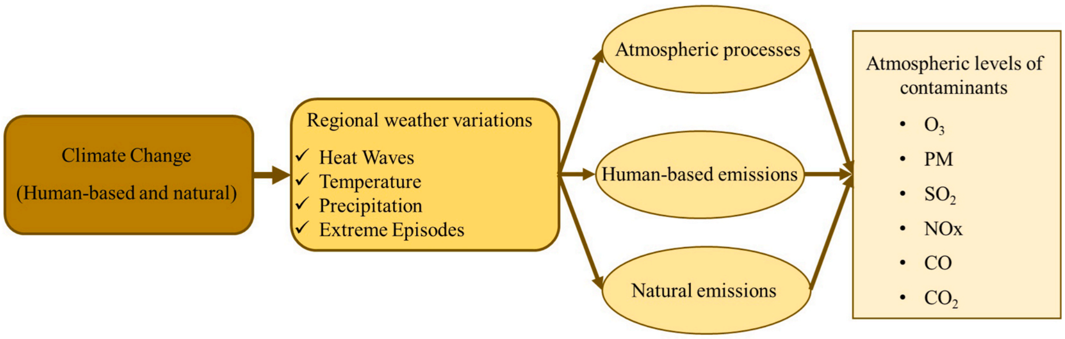

Fig. 3. Framework of climate change and its attributions to pollutant concentrations of the outdoor air, Re-illustration from Ref. [55].

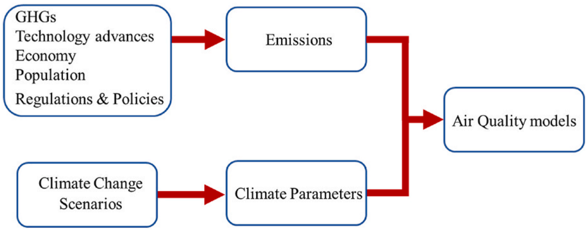

Fig. 4. General data-flow hierarchy for obtaining an air quality model.

numerous sources. Eulerian grid models are the most complex, but potentially the most powerful air quality models involving the least-restrictive assumptions [60].

Employing representative CTMs, such as CMAQ and WRF-Chem, are typical methods for urban air quality prediction.

Along with the 4th industrial revolution, newly valuable literature reviews have been carried out to provide detailed insights into the performance analysis of AI, machine learning, and ANNs in terms of a numerical modeling approach for future outdoor air pollution prediction [61–63].

2.1.3.3. Future indoor climate. There are several approaches available to predict future indoor climate. The future indoor climate of buildings can be estimated by building simulations fed with input data from global climate models. Building simulations to obtain future indoor climate can be carried out by well-known software such as EnergyPluse, TRANSYS, MATLAB, CFD-based models, etc. One additional approach is implementing the indoor-to-outdoor (I/O) temperature ratios [2,19]. The other methods are applying machine learning predictive models to predict future indoor climate. In this approach, the common choice for indoor climate prediction is the ANN, particularly the Recurrent Neural Network (RNN) variants like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) [64].

2.1.3.4. Future building characteristics. Warmer seasons under climate change conditions may lead to increased operation of natural ventilation, while the application of cooling systems during extreme heat events may reduce natural ventilation use. The strategies for building adaptation comprise strengthening the insulations, implementing new materials, and intelligent building technologies, and potentially adopting extended utilization of air conditioning systems during summers as compared to the present practices [17].

The main motivation for the development of future building retrofit scenarios in terms of climate mitigation and adaptations, is improving the Indoor Environmental Quality (IEQ) and building energy performance [65,66]. Generally, the building retrofit action plans impact the IAQ in three fashions, as follows:

1. Transition from fossil fuel-consuming heating (& cooking) systems to electric and renewable- or sustainable-based systems, that enhance the IAQ by eliminating pollutant emission sources.
2. Advancement of HVAC control strategies based on optimal indoor thermal comfort which potentially reduces the IAQ due to relatively reduced AERs. Similarly, reduced use of mechanical ventilation or shift to natural ventilation (in summers), which can potentially reduce the minimum acceptable indoor airflow rates, are settled in this category.
3. Increased air tightness and reduced infiltration/exfiltration rates of buildings to conserve indoor air thermal capacity and prevent heat losses, which leads to reduced IAQ levels.

Commonly, the abovementioned scenarios are defined and aimed by regional building codes and energy sectors, applicable as input data for IAQ and whole building simulations.

2.1.3.5. Future occupants' behavior. Within the multidisciplinary fields of indoor chemistry and building physics, there is increasing attention to occupants' behavior due to its significance in IAQ and building energy performance [67,68]. The study of occupant behavior involves disciplines ranging from building physics to human biology, to evaluate IEQ [69,70]. Three distinct approaches to this end are as follows:

1. Deterministic methods via established scenarios and behavioral rules (including but not limited to occupancy degree, indoor activity type/schedule, and airflow rate gain by ventilation patterns)
2. Numerical methods based on experimental observations (e.g., surveys, automated mechanical and natural ventilation loggers, etc.)
3. In the context of climate change, future occupants' behavior scenarios are practically defined in terms of variant ventilation processes and operations types/periods, variant residence time, and cooking emissions.

2.2. Demonstrative case study

In the supplementary file of this paper (see the supplementary file), a full demonstrative case study with the aim of practical implementation of the framework is presented. The case study focuses on the quantitative analysis of climate change impacts on IAQ. The IAQ experiments were conducted in a naturally ventilated house (+2 exhaust fans) in the summer of 2021 (see Section S1). The test house was located in Arlon, Belgium (the first floor of a residential building), and was renovated in 2020. The IAQ model design was performed in CONTAM (see the supplementary file, Section S3). Considering three different climate scenarios (IPCC: SSPs 2–4.5, 3–7.0, and 5–8.5), the future regional weather data were obtained by meteorological modeling. Future regional air pollution data were obtained by deep learning (see the supplementary file, Section S4).

3. Results of the demonstrative case study

As a practical implementation of the framework, all corresponding sections were executed within a demonstrative case study (see the supplementary file, Sections S1, S3 & S4). Afterward, the gathered future input data fed into the validated and calibrated CONTAM IAQ model (basis-year 2021). The occupant's behavior and ventilation patterns were assumed fixed. Predicting future IAQ levels indicated elevated concentrations of NO_2, PM_{10}, and O_3; decreased levels of $PM_{2.5}$ and NO; and no variations in CO levels, for our case study. Further detailed results are available in the supplementary file (see the supplementary file, Section S5).

3.1. Findings & recommendation

Climate change can affect the IAQ due to heat and mass transfers between indoor and outdoor environments. To mitigate climate change impacts and adapt buildings to the changing environment, adjustments in building elements and correction of occupants' behavior are expected correspondingly. Therefore, in the lack of a systematic solution for quantifying the effects of future climate scenarios on IAQ, an integral (summative) framework is introduced in a systematic manner. Whether an IAQ model is designed based on a limited number of case studies, or is developed based on representative characteristics and elements, obtaining real measured data is a critical integral step for empirical validation and for defining generalized parameters. Therefore, the presented framework is structured with a permanent IAQ measurement step.

As presented in the demonstrative case study of this research (see the supplementary file), after confirming the performance of LCSs in the "sensor calibration study" [71], and subsequently conducting tests in the "IAQ measurement campaign", the performance of the designed IAQ model in CONTAM was explored.

As shown in Fig. S3., the continuous emission rates which were calculated based on the mass-balance approach led to more realistic continuum results indicating improved model performance (compared to literature-extracted emission rates). Regarding the IAQ model validation (performance evaluation), as can be seen in Table S3., statistical compliance with ASTM-D5157 [72] criteria varies among different pollutants. The results based on the continuous emission rates approach are better to some extent, specifically with improved overall mean r (average r of all contaminants) from 0.54 to 0.72.

The interpretation of scatter plots of the CONTAM results against measured values (see Fig. S4.) suggests that: 1. there is a positive correlation among all estimated and measured values, for both emission rate approaches, 2. in the second approach (see Fig. S4b.) the correlation between CONTAM results and measured values demonstrates a significant improvement (stronger relationship) even in a longer period, but not for PM and O_3. This could be due to the strong relatively outdoor sources of these contaminants, outside of the indoor emission episodes, and the uncertainties in the questionnaire completion (accurate record of natural ventilation and exhaust fans operation).

It should be mentioned that although some criteria do not meet the high expectations of D5157, considering the long-term comprehensive experiment duration and involved uncertainties (e.g., sensors performance, questionnaire, model parameters, etc.), still the model performance is reasonable. Fig. 5 illustrates the comparison of pollutant concentration box plots of CONTAM results against measured values of the case study, for both emission rate approaches. The CONTAM results are well within the magnitudes and ranges of those by real measurements in both emission rate approaches. As presented in Fig. 5b, the levels of the modeled and observed average concentrations for VOCs: (59.37 and 56.78 ppb), and O_3: (59.88 and 57.52 μg/m^3), demonstrate a very close agreement from the average perspective (same pattern for Fig. 5a). Strictly speaking, while the D5157 statistical criteria can support understanding the advantages/disadvantages of a designed IAQ model, one additional general assessment can be the comparison of whole datasets in terms of average values. This inclusive assessment confirms that the model's strength to estimate the relative outputs (when different variables are varied), has a consistent agreement (e.g., exhaust fans and natural ventilation performances or existence of emission sources based on occupant activities). Concerning the satisfactory model performance with calculated emission rates by the mass-balance approach, the overall mean FB value (average FB of all contaminants) of 0.11, indicates a minimum systematic error.

Concerning outdoor air pollution, although, the emissions of key pollutants in Europe have almost decreased in the past decade, it is still an important concern. This is because of the complexities of the processes related to emissions and air quality, especially

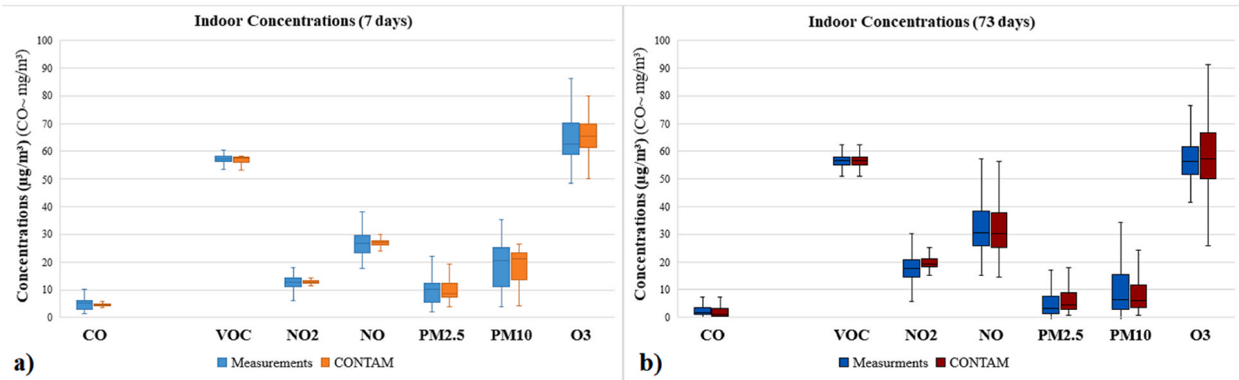

Fig. 5. CONTAM results vs. indoor measurements of the case study, a) 7 days, 18–24 July 2021, average emission rates, and b) 73 days, 20 June - 31 August 2021, mass-balance approach emission rates.

interactions with meteorology, in which spatial decrease of emissions, do not necessarily reduce atmospheric pollutant levels [73,74]. The outdoor concentration of major contaminants (with outdoor sources) is estimated to reduce in the future by the 2050s and 2100s, but PM_{10} and O_3. The predicted reduction in outdoor pollution concentration combined with the natural ventilation system will, on average, contribute to the reduction of indoor pollutant concentrations, which are infiltrated from outdoors. Two remarkable exceptions are O_3 and PM_{10}, which are expected to elevate in the future climate trends, thus leading to an increase in their levels which infiltrate and remain in buildings [75].

Because of well-controlled emissions of CO, it is considered a pollutant with persistent indoor sources. However, CO had presented the lowest correlation with outdoor weather among all pollutants within our indoor measurement campaigns which led to the lowest "future outdoor CO" prediction performance by the deep learner model among all stations (see Table S5). On the whole, average outdoor CO is predicted to remain constant (or so) by the 2050s and 2100s and the increase in the indoor levels is only due to the contribution of indoor sources of the Arlon case-study basis model. For contaminants with primarily periodic indoor sources such as $PM_{2.5}$, PM_{10}, and NO, the main contributions are from indoor sources. $PM_{2.5}$ and NO mean indoor levels are marginally decreased in future climate trends. This reduction is due to natural ventilation and a slight decrease in average outdoor $PM_{2.5}$ and NO levels. For the PM_{10}, the average outdoor concentrations decrease slightly till the 2050s and then increase to some extent till the 2100s and the same pattern is followed for the indoor average PM_{10} levels. The prediction of future outdoor PM highly relies on key assumptions in the prediction approach. There have been reported several different and contradictory results in terms of future outdoor PM concentration predictions over different regions [76,77]. The increase in PM_{10} outdoor concentration (relatively SSP5>3>2) can be explained by the greater impacts of higher temperatures on PM_{10} emission and water evaporation rates. According to the key findings of a study conducted in collaboration with the Belgian Interregional Environment Agency (IRCEL - CELINE) in 2010, among various elements; climate change is capable of moderately or fully undoing the valuable impacts of expected contaminant emission reductions due to higher temperatures (increased kinetic of atmospheric chemistry) and the incidence of droughts (lack of sufficient precipitation) [76,78,79].

For pollutants with primarily intermittent outdoor sources including NO_2 and O_3, the main indoor contributions are from outdoor sources for O_3, and relatively fewer contributions from outdoor sources for NO_2. NO_2 and O_3 average indoor concentrations are increased in future climate scenarios.

To summarize the significant recommendations, the list below is provided:

- It is recommended to implement the proposed framework to quantitatively assess the impacts of climate change and possible future scenarios on IAQ. Our framework presents modular solutions among all available approaches to address the research objective, rather than a singular answer.
- It is recommended to use calibrated LCSs for IAQ experiments due to their simple application in concurrent multi-zone measurements. Considering, the usual drift of the sensors, re-calibration must be managed each year for PM sensors (auto-calibrated, if drift data show no need to recalibrate before 12 months) and each 6 months for the others.
- It is recommended to use the CONTAM IAQ model due to its prominent design and coupling capabilities, as well as being time and cost-efficient.
- It is recommended to perform the emission rate determination tests under highly controlled conditions, due to the sensitive impact it has on the results.

3.2. Strengths & limitations

There are rising IAQ concerns about both GHG emissions and heatwave risks (direct/indirect), which are expected to take place to a greater extent in future climate scenarios. There is no common guidance to examine the climate change effects on IAQ quantitatively, to date. To overcome this lack, this paper introduces a systematic framework that can be followed step by step to evaluate climatological and building retrofit effects, computably. The first strength of this paper is rooted in the robust literature study and consideration of all accomplished distinct projects on the topic, worldwide. The typical implementation of the framework is also demonstrated in a case study. While the framework presents multiple choices for researchers at each section and step, the case study's focus was on the most time and cost-efficient approach selection for all three steps. In the first step calibrated LCSs were utilized, in the second step multi-zone indoor air modeling software, CONTAM was employed, and for the last step, a deep learner neural network was used to obtain future outdoor air pollution. None of the previous studies aiming at climate change effects on IAQ has carried out all these aforementioned techniques together.

However, the case study has some limitations. First, as it has been previously discussed in the literature by principal studies [80,81], absolute validation of a multiplex model, such as CONTAM, is not feasible due to countless practical arrangements that IAQ specialists can design for a real-world case study, as well as uncertainties in the model input parameters.

Second, focusing solely on a case study with natural ventilation type led to ignoring the potential HVAC strategies and the linked energy performance aspects. Although exhaust fans in the case study are mechanical-type ventilations, the whole-house mechanical ventilation systems were the point of concern in the aforementioned limitation. Lastly, a couple of typical IAQ experiments such as the tracer gas decay test (demanded by ASTM-D5157), and blower door test can provide more robust input parameters for the model. Correspondingly, more accurate experiments are recommended to master the limitations of this case study.

3.3. Implication on practice & future research

One of the outcomes of this present work is to understand and incorporate the suggested framework and recommendations into forthcoming updates of building regulations at the national, regional, or local levels. There are limited guidelines (internationally/

nationally) concerning the IAQ, which focus on Exposure Limit Values (ELVs) and the minimum required AERs, and no consideration for climate change and future scenarios.

Furthermore, while employing multi-zone models offers time and cost-efficient valuable insights into the IAQ performance, future studies are advised to employ genuine multi-criteria (e.g., construction year, architecture type, energy performance) reference building models for generalized assessments of building house stocks, at various scales.

In contrast to mechanistic IAQ models, which define the connection between inputs and outputs through governing mechanisms, statistical models aim to establish an optimal link between inputs and outputs to represent the measured data. Hence, it is reasonable to develop a hybrid approach involving both mechanistic and statistical models for IAQ evaluation within residential premises. In this approach, the mechanistic model handles the physical and chemical phenomena, while the statistical model tackles human behavior aspects.

Moreover, it is advisable that forthcoming studies consider the development of IAQ performance indexes linked to the influential climatological elements. The introduced IAQ metric should comprise a broader range of climatological parameters to more accurately capture the interplay between climate and IAQ. Additionally, there is a need to establish a precise post-processing procedure for conducting sensitivity and optimization analyses. This would not only refine the framework but also broaden its scope by enabling the optimization of required AERs and HVAC control strategies for various building types and climates.

4. Conclusions

The work presented in this study supports the principles of the OCCuPANt project [82]. Hence, a systematic framework for quantitative assessment of the IAQ under the potential impacts of future climate scenarios is introduced. Afterward, a practical implementation of the framework is demonstrated within a case study research. To this end, calibrated indoor air monitoring devices based on LCSs were utilized for long-term experiments of 73 days in a naturally ventilated house (+2 exhaust fans), in Arlon, Belgium (summer 2021). A poly-contaminant multi-zone IAQ design is developed in CONTAM to estimate the pollutants' temporal profiles of the test house. The mean concentrations of experiments and the model outputs were similar at the 77 % level of confidence for PM, 83 % for CO, and +90 % for other contaminants; representing a consistent agreement. The future ambient climate data was obtained from the historical and future weather database for dynamic building modeling in Belgium by the regional climate model "MAR", with a spatial resolution of 5 km. Three different future outdoor climate scenarios were taken into account based on SSPs 2–4.5, 3–7.0, and 5–8.5. Future outdoor air pollution data was obtained by a CNN-BiLSTM deep learner network. The learning, validation, and test processes of the ANN were carried out with the aid of the past 15 years (2008–2022) hourly outdoor air pollution and climate data of 5 different locations in Belgium. The mean indoor level of contaminants, those with dominant indoor origins not only for CO but also for VOCs (which was not considered in this study due to the lack of outdoor data) show the significance of ranking extensive endeavors to decrease and control indoor emission sources. Hence, the advancement of ventilation systems, and the application of high-performance air purifiers (cleaners) to increase the IAQ levels in residential buildings are advised.

We obtained a set of final rather than random results, based on the mean hypothesis for model input elements which do not explain the essential incertitude in the estimations. Also, we assumed some parameters to be fixed in the future, even though they seem to be different and changed to a certain level. The taken assumptions allowed a quantitative evaluation of climate change effects on IAQ, for the mid-term and long-term future by a limited set of accessible infrastructures and resources.

CRediT authorship contribution statement

Mohsen Pourkiaei: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ramin Rahif:** Writing – review & editing, Formal analysis, Data curation. **Claudia Falzone:** Writing – review & editing. **Essam Elnagar:** Writing – review & editing. **Sébastien Doutreloup:** Writing – review & editing. **Justin Martin:** Writing – review & editing. **Xavier Fettweis:** Validation, Resources. **Vincent Lemort:** Validation. **Shady Attia:** Writing – review & editing, Validation, Resources, Funding acquisition, Conceptualization. **Anne-Claude Romain:** Writing – review & editing, Validation, Supervision, Resources, Project administration.

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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Appendix A. Supplementary data

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