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Micro-Climate Building Context Visualization

A pipeline for generating buildings' environmental context maps using numerical simulation data

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Residential buildings are responsible for a considerable share of energy consumption and carbon emission. To decarbonize by 2050, as agreed in the Paris Climate Accord, immediate action for lowering the environmental impact of the building sector is needed. Environmental building design is a promising path, particularly during the early-stage design when design decisions are more impactful and long-lasting. One of the initial steps in the building design process is site assessment, during which the building context and environmental factors are to be evaluated. The surrounding environment plays a critical role in the building's energy performance and the thermal, visual, and acoustic comfort of its occupants. We choose quantitative approaches to study the complexity of the environmental design with respect to the building context by analyzing environmental cues embedded in architectural drawings that have been given less attention in previous studies. Nevertheless, disclosing site-specific geolocation data of buildings, more specifically residential type, is often challenging due to privacy issues. Therefore, there is a lack of context-related metadata in the current architectural datasets. Whereas simulation data are more available and provide a wealth of contextual information, however, it is less appealing for architects to interpret design patterns from extensive simulation figures. This research focuses on developing an interpretable visualization of the building's micro-climate context from environmental simulation data without direct access to the geolocation of the site. The environmental context visualization is created from daylight, view, and noise from 3088 multifamily housing presented in the Swiss Buildings data set, merely based on available simulation data. The presented pipeline in this study facilitates the employment of existing simulation data in the built environment datasets while circumventing the concerns associated with geolocation data exposure. Further, the generated visualizations may be used to develop computer vision models for environmental assessments of building layout design.

Keywords: *Building Context, Environmental Design, Data Visualization, Big Data, Decarbonizing.*

INTRODUCTION

Globally, the buildings and the construction industry account for 36% of final energy demand and almost 40% of energy- and process-related emissions, of which the share of residential buildings corresponds to 22% and 17%, respectively (IEA, 2019). Many studies have been conducted to find solutions for energy-efficient buildings, particularly during the design phase (Pacheco *et al.*, 2012). The early-stage design decisions, including the building orientation and allocation of interior spaces highly affect the building's performance in the subsequent design steps (Li *et al.*, 2023). Moreover, the life-cycle environmental performance of buildings is greatly influenced by the decisions made at the initial design phases (Feng *et al.*, 2019). Environmental factors such as daylight conditions, noise sources, and view to the outdoors are elements to be addressed for the sustainable development goals. Spatial zoning (AIA ETN, 2022), which involves assigning functions to different zones of the building, is a crucial step in the schematic design stage of building design, also known as functional layout (FL) design (Zawidzki and Szklarski, 2020). In addition to meeting functional needs, the FL design decisions should address the environmental requirements of each space. Thus, incorporating environmental factors in the building design process as early as possible can lead to more lasting positive impact.

The building is often contextualized by its geographic location (Starzyńska-Grześ *et al.*, 2023), which is a critical information for environmental design goals, by specifying the surroundings and the local climate (Quan *et al.*, 2014). Attention has been drawn to investigating the impact of context and inter-building relationships on building retrofit strategies and energy use ((Walker *et al.*, 2022), (Pisello *et al.*, 2012), (Pisello *et al.*, 2014), and (Ascione *et al.*, 2020)). However, efforts are highly scarce in evaluating the potential impacts of the building's surrounding on the internal space layout.

Data in the built environment

Different formats of data are produced during an architectural design process, such as numerical data of simulation results or metered data of sensors, textual data regarding materials and annotations of drawings, and visual data of architectural technical drawings, 3D models and simulation maps. Of all different types of data produced during an architectural design process, image type data dominates. More specifically during the early-stage design steps, data is mostly presented in conceptual diagrams in the form of undetailed images.

One of the effective methods of representing big data is through visualizing. Data visualizations facilitate representation of facts, comparison of data, and analysis of patterns. However, attention must be paid in creating data visualization, as the way data is presented influence the way the data is interpreted by users (Lee-Robbins and Adar, 2023). In the field of landscape architecture and GIS area, (Fricker and Munkel, 2022) highlighted benefits of developing interactive maps of project sites. The aim of research was to control interactions between data visualizations and its influence on landscape design. Therefore, there is a significant potential in creating interactive visualizations of big data in architecture and the built environment, assisting designers in decision-making process.

Considerable body of study has employed data-driven approach for predicting the energy and environmental performance of buildings ((Singh *et al.*, 2021), (Singh *et al.*, 2022), and (Olu-Ajayi *et al.*, 2022)). Despite data abundance, gaining benefits of architectural data for the purpose of data-driven analysis is not straightforward. Lack of context and metadata in available datasets in built environment prevents generalizing the results of a data-driven model across different climates and countries (Starzyńska-Grześ *et al.*, 2023).

RELATED STUDIES

Studies have investigated the effect of building context and inter-building relations on the building's energy and environmental performance. The effect of context has shown to be dynamic, varying under different climatic conditions and seasons (Pisello *et al.*, 2012). Context-related influences can also be explored at different scales, ranging from countries and cities to districts and building sites.

Highlighting the necessity of decarbonization strategies in building stock, (Walker *et al.*, 2022) investigated the robustness of different retrofit strategies in six European contexts. Results confirmed that the performance of a certain retrofit strategy is considerably context-sensitive. In the case of energy modelling of high-rise buildings, the crucial effect of urban context has not been included, except for few studies such as (Liu and Lee, 2020), (Aflaki *et al.*, 2019), and (Samuelson *et al.*, 2016). This leads to inaccuracies in reported environmental results. In another study, the energy performance of a realistic block of twenty single-family houses under different climatic contexts of USA was analyzed by (Pisello *et al.*, 2012). Authors reported inaccuracies of energy modelling up to 42% for the case of Miami in summer and up to 22% for the case of Minneapolis in winter. A hybrid simulation and data-driven approach was employed by (Nutkiewicz *et al.*, 2021) to explore the influence of urban context on building energy retrofit performance. According to the evaluation of the suggested approach on 29 densely co-located buildings in California, authors reported that accounting for urban context can compound the impact of retrofits on individual buildings by up to 7.4%. In different local climate zones of South Korea, (Bansal and Quan, 2022) investigated the impact of urban form on building characteristics and energy use. Results demonstrated that different contextual urban forms affect the buildings' energy use not only directly, but also indirectly through the intermediary impact of building characteristics.

On the district level, two building density alternatives in the climatic context of France were compared based on solar irradiance, wind airflows, building indoor temperatures and energy demand in a study conducted by (Gros *et al.*, 2016). Analysis results of the reference and densified districts showed considerable variations; namely, the prevailing wind velocity reduction of up to 80% between the buildings. Moreover, a decrease of about 7% in the number of sunshine duration on the existing building in the surrounding was reported. In another study on building site level, a framework for optimizing the architectural functional layout based on context-related metrics was proposed by (Zawidzki and Szklarski, 2020). The suggested method incorporates site-specific objectives including solar insolation, outside view and external noise at the early stage building design. The optimal design of functional layout in this study is defined by the weights which are assigned to each environmental factor based on user preference. In another study in the climatic context of Berlin, (Agirbas, 2022) considered three objectives of daylighting, acoustic performance, and floor area for optimizing office space conceptual forms. The optimization process was performed for three different case studies with multiple visual- and acoustic-related metrics. Also, site constraints including boundaries and distance of the space from the boundary were included.

Different data types among the datasets on city, district, and building levels enable various analysis (Rahbar *et al.*, 2022). Qualitative analysis of urban environments is one of the main areas in which visual data can be vastly implemented (Starzyńska-Grześ *et al.*, 2023). Publicly available datasets on city, district, and building levels offer a lot of analysis on the big data in the built environments ((Pizarro *et al.*, 2022) and (Wu *et al.*, 2022)). However, there is a lack of comprehensive datasets including contextual metadata and curated specifically for problems in the built environment. This calls for expanding current datasets in architecture and the built environment towards integrating macro- and micro-climatic features.

Contributions and scope

In this study, a methodology is proposed to facilitate the integration of environmental building simulation results into one of the largest available datasets in architecture and the built environment by means of visualization of numerical simulation data. The aim is to represent a given building's context, without accessing to the geolocation of the site. Although the effect of context can be studied in a broad scale as in (Walker et al., 2022), in this study the term is used to represent the building's surrounding environment including sky and

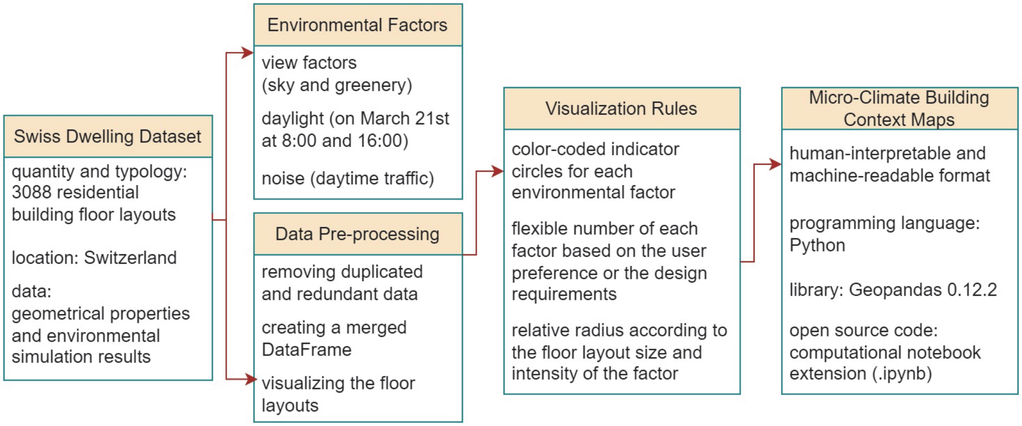

Figure 1
micro-climatic building context visualization pipeline

greenery views, daylight condition and traffic noise during the day time. The factors are selected in such a way that both visual and acoustic performance metrics are included.

In this research, the Swiss Dwelling dataset (Standfest et al., 2022) containing floor plans of 3088 residential buildings in Switzerland and their corresponding environmental simulation results is used as analysis material.

The main contributions of this research are as follows:

- Introducing visualization of numerical simulation data as a more intuitive, and human-interpretable medium for architects in environmental design
- Augmenting context-related visual metadata to the Swiss Dwellings data set while circumventing geo-location data exposure
- Setting up a visualization pipeline including open-source python code to automate the meta-data generation

METHOD

In this study, a pipeline of micro-climate building context visualization is proposed using Python programming language. The presented method is then applied to the Swiss Dwelling dataset v2.2.1 as the material for clarification of the pipeline (Figure 1).

Dataset

The latest version of the Swiss Dwelling dataset includes four tabular data files including “Geometries”, “Simulations”, “Location Properties”, and “Location Ratings”. The first contains the geometries of all areas, walls, railings, columns, windows, doors and fine-grained features (sinks, bathtubs, etc.) of each apartment in the specified sites. Different levels of identification methods for referencing spaces are defined, ranging from site ids to internal area identities. The element’s geometry is presented as a WKT (well-known text), which is markup language for representing vector geometry objects.

Beside the geometrical model, the simulation data on the visual, acoustic, solar, layout, and connectivity-related characteristics of the apartments are also provided in the “simulations.csv” file. The file contains the simulation data aggregated on a per-area basis. The “location” files consist of monthly and annual data on temperature, sunshine duration, and precipitation and also the 10-minute walkshed infrastructure in each site. The “location rating” file contains rating data on the overall quality of living conditions in each site, such as service and leisure qualities. Since the aim of the current study is to retrieve the environmental factors of buildings' contexts, the first two files (i.e., "Geometries" and "Simulations") are the main data sources.

Data preparation

Data cleaning and pre-processing are performed for data and metadata consistency. In data cleaning process, redundant data is removed and incorrect, incomplete, irrelevant, or improperly formatted data is modified (Recht *et al.*, 2019). The data cleaning extends to fixing spelling and syntax errors, and standardizing data. Data pre-processing is tailored towards the selection, manipulation, and format processing of for the downstream task.

In this study, data cleaning and pre-processing were performed with the main goal of merging the geometrical and simulation data. Therefore, after filtering the required features in both the geometry and the simulation database files, the two files were merged by a common feature of area identity. Consequently, the merged data frame contained the following features: site, building, floor, unit, apartment, and area identities, entity type, and sub-type, plus simulation results of sky view, greenery view, daylight on march 21st at 8:00 and 16:00, and traffic noise level during the day. After merging, rows with duplicated or incomplete values were dropped and only spaces with the "area" sub-type were kept. In other words, separators such as external and internal walls, openings such as windows, and features such as sinks and bathtubs were omitted.

After the data pre-processing step, the data frame was ready to be converted to the format by which the visualizations are feasible. In this step, first some tests were performed to find a practical way of visualizing geometry column in the format of WKT. The main challenge was converting the string representation of geometries to Polygon type. For this purpose, the GeoPandas library for Python was used ("GeoPandas 0.12.2", 2022). Consequently, applying geospatial operations is conveniently feasible. This library allows plotting and spatial operations on geometric data types, which is practical for working with floor layout visual data in architectural drawing datasets. Figure 2 shows a sample visualization of a certain site. The +y direction points northwards, the +x direction points eastwards.

Figure 2
Visualization of a sample site in the Swiss Dwelling dataset

Table 1
color-coding rule of environmental factors in the micro-climate building context visualizations

Environmental factor	color-code	Number of indicator circles
View Sky	Grey	4
View Greenery	Green	2
Daylight on March 21st at 8:00	Yellow	2
Daylight on March 21st at 16:00	Yellow	2
Daytime traffic noise	Red	2

Data semiotics

The elements connecting the interior and exterior of a building, and hence conveyors of information from the context to the inside are balconies and windows. To achieve the greatest similarity in terms of the building's surroundings, the highest values of each environmental metric were utilized for every floor across all buildings. This means that the values corresponding to the grid located either on the balcony or near the window of each space were used. For instance, the status of the view to the greenery in each site from a specific space located on a certain floor of a building is most similarly related to the one corresponding to the nearest grid to the window.

As representatives of occupants' visual comfort metrics, daylight and view factors are selected. More specifically, two hours (8:00 and 16:00) on March 21st are selected in order to take orientation-related daylighting condition into account. Also, the daytime traffic noise was selected as a representative of occupants' acoustic comfort. For each environmental factor, the largest values are detected and displayed by a color-coded circle on their corresponding area. The center of each circle is located on the centroid of the associated area and the radius is proportionate to the value of the metric and the size of the floor layout. To make the indicator circles comparable in size, each environmental factor was first normalized between 0 and 1 and then multiplied by the base radius, resulting in final value of the radius. The base radius is calculated for each layout and is equal to 15% of the maximum length of floor boundary along x- or y-axis. The number of indicator circles used in this study and color-coding rule is brought in table 1. It is also possible to change the number of indicator circles based on the user preference or the design specifications. An alpha value of 0.5 is considered for all color-coded circles and the floor layout to make the probable overlapping of circles visible.

RESULTS

After applying the method described in the "Data semiotics" section for a number of sample floor identities, the same procedure was followed for all floor layouts in the dataset. The resulting visualizations for two sample floor layouts are shown in Figure 3 and Figure 4. The first layout is located in a site elongated in Northwest-Southeast axis. As it is shown in Figure 3, the Southwestern oriented spaces in this floor have higher view to sky potential, which demonstrates less blockage of view by nearby buildings. Access to daylight is more convenient in parts of south, north, and southwest of the floor. Moreover, the spaces in south and southwest parts have higher view to greenery. In addition, daytime traffic noise level during the day is higher on southeastern and eastern parts of the site. The change in the indicator circles color shows the overlap of environmental factors. Also, the radius of each indicator circle is proportionate to the corresponding environmental factor value. For instance, access to daylight is more in southern parts of the floor (i.e., the daylight indicator circle has higher radius), and the spaces located in western side of the layout have all sky view, greenery view, and access to daylight potential.

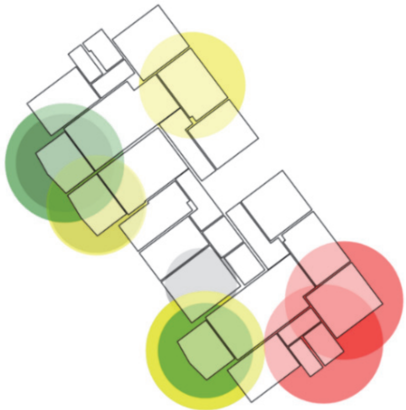

Figure 3
micro-climate context visualization of a sample floor layout elongated in northwest-southeast axis

Figure 4
micro-climate context visualization of a sample floor layout elongated approximately in north-south axis

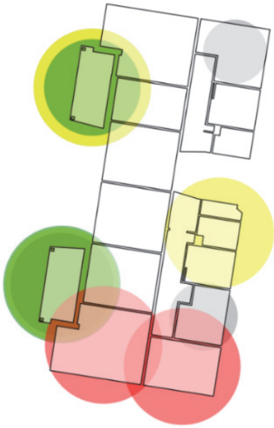

Figure 5
micro-climatic comparison of two different floors in a same building and site – upper map corresponding to upper floor and lower map corresponding to lower floor

Another example of micro-climatic context visualization of a floor layout elongated in approximately north-south axis is demonstrated in Figure 5. In this case, concentration of environmental indicator circles shows the higher potential of daylight, sky and greenery view in southwestern spaces. The daytime traffic noise level is much higher in southern side of the site, whereas spaces located on the northwestern parts of the site can benefit from view to greenery and access to daylight.

The generated maps highlight the importance of taking the environmental factors more carefully into account. The proof is that due to the unique context for each site, different floors in the same building have different environmental conditions. An example is shown in figure 4, where the different maps for two floor layouts in the same building identity are demonstrated. Both layouts have higher greenery view on the northeastern side, while the distribution of daylight, sky view, and more noticeably daytime traffic noise level varies. The possible reasons lies within change in surrounding buildings height and distance from the intended building, which consequently affect the accessibility of environmental factors.

DISCUSSION

Addressing the environmental design of multi-family housing is of great importance, since around three-quarters of buildings in the European Union are residential (European Academies Science Advisory Council, 2021). Therefore, it is worthwhile to expand the datasets on residential buildings as the starting point.

In this study, a pipeline for micro-climatic context visualization of residential buildings is proposed. The merged data-frame containing data on geometry and environmental simulation results is used as the input. The color-coded maps of each floor layouts in the Swiss Dwelling database are regarded as output. The method can also be conveniently applied to other building types in case of dataset availability.

The proposed method will further affect the integration of context in designing space layout, which will impact the energy performance of the building (Du *et al.*, 2020). Also, different machine learning tasks, including image classification, object detection, semantic segmentation, or scene reconstruction can be formulated on urban scene and building scale using the generated micro-climate context image data (Starzyńska-Grześ *et al.*, 2023).

Visualization methods offers considerable benefits in terms of understanding and analyzing big data. However, data visualizations are prone to be influenced by designers' biases, backgrounds and personal opinions (Lee-Robbins and Adar, 2023). Accordingly, the choice of certain environmental factors including sky and greenery view factors, daylight on march 21st at 8:00 and 16:00, and daytime traffic noise among all the factors in the original dataset might indirectly affect further use of the generated maps.

The Future perspectives of the current study can be envisioned in a learning-based framework. Such that the parameters of the generated maps will be learned by a neural network. The generated maps of micro-climatic context representation can further be used as input for machine learning models to be trained on. As a prerequisite step, the maps should be firstly filtered to separate environmentally-oriented designs from the rest. Accordingly, the machine learning model will be trained based on proper data and will be able to extract the environmental clues more efficiently. The models can be trained with the aim of either analysis or generative approach.

CONCLUSION

Benchmark datasets in architectural design are scarce due to a lack of standardization, different annotation styles, and a lack of metadata. The privacy issue makes it challenging to disclose geolocation data of specific buildings, especially residential types. As a result, architectural datasets lack context-related metadata. In this study, the pipeline of micro-climatic context visualization of each floor layout in 3088 buildings in the Swiss Building dataset is presented. The main contribution of the proposed methodology is to expand one of the largest available datasets in architecture and built environment towards the environmental building design approach. The visualizations are provided in a way that can be both human-interpretable and machine-readable for further decision-making tasks.

The color-coded micro-climatic maps will facilitate the environmental analysis of floor layouts. The generated maps can be further used as input for including environmental impacts of context on the design process, while circumventing geo-location data exposure of buildings. In addition, a learning-based framework can be developed in such a way that the parameters of current visualizations will be learned by a neural network. The pipeline code and samples of the generated maps can be found at: https://github.com/Fatemeh-Mostafavi/Micro-Climate-Building-Context-Visualization-

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